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Research paper

Design limits and investment risks of mid-term storage under uncertain market conditions

Jonathan Stelzer [a],*, Katharina Esser [b], Thorsten Weiskopf [a], Armin Ardone [a], Valentin Bertsch [b], Wolf Fichtner [a]

[a] Chair of Energy Economics, Karlsruhe Institute for Technology (KIT), Hertzstraße 16, Karlsruhe, 76137, Germany
[b] Chair of Energy Systems and Energy Economics, Ruhr Universität Bochum, Universitätsstraße 150, Bochum, 44801, Germany

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ABSTRACT

The transition to a net-zero energy system with high shares of variable renewables increases the need for flexibility beyond short-term batteries and seasonal hydrogen storage. Emerging storage technologies with discharge durations from several hours to a few days may fill this mid-term segment due to their cost structures, but their economic viability under uncertain future market conditions remains unclear. This study assesses which combinations of energy-to-power ratios (8–168 h) and round-trip efficiencies (10–100%) enable profitable and robust investments from an individual investor's perspective, by evaluating storage configurations with an agent-based electricity market model that incorporates mean-reverting stochastic fuel prices and renewable generation. The results show that the marginal benefit of additional storage declines sharply with increasing energy-to-power ratios, increasing maximum capital expenditures by approximately 25% from 24 to 168 h. In contrast, increasing the round-trip efficiency from 40% to 60% can reduce downside risk, measured as the difference between expected contribution margin and conditional value at risk, by 5% and increase the maximum allowable capital expenditure by about 61% within the analysed cases. Consequently, only configurations with sufficiently low energy-specific capital costs and moderate to high efficiencies remain economically competitive in the mid-term segment. This work demonstrates how balancing efficiency, costs, and storage duration drive mid-term storage competitiveness, highlighting their critical influence on performance, while introducing risk-based assessments to quantitatively evaluate a comprehensive parameter space and its impact on investment risk.

1. Introduction

To achieve the Paris Agreement's objective of limiting global warming to 1.5 °C above pre-industrial levels, global greenhouse gas emissions must reach net zero by mid-century [1]. In the electricity sector, this leads to a rapid expansion of variable renewable energy sources, which already induced profound structural changes [2]. Increasing renewable shares complicates the challenge of balancing supply and demand, thereby requiring enhanced system flexibility. Besides flexible conventional generation (e.g., hydrogen-ready gas turbines), additional flexibility can be provided by electricity storage, demand-side response, and sector coupling, which enable load shifting and enhance grid stability [3]. While battery storage provides short-term flexibility by mitigating imbalances between surplus and deficit renewable generation, hydrogen-fired power plants and electrolysers are projected to offer seasonal storage solutions, complementing established resources such as hydropower [4]. However, both technologies face constraints: lithium-ion batteries remain costly for long storage durations [5] and rely on critical raw materials [6], while hydrogen costs and quantities are uncertain [7] and electrolyser deployment is still in early stages [8]. This creates an opportunity for emerging storage technologies whose cost structures position them between short-duration and seasonal storage solutions [5]. In this context, technologies designed to continuously discharge energy from several hours up to a week are referred to as mid-term storage. Evaluating the technical design parameters of emerging energy storage technologies is therefore crucial to assess their suitability and economic potential.

However, metrics such as the Levelized Cost of Storage (LCOS) offer only limited guidance. Being cost-based, LCOS does not adequately capture the revenue potential of storage technologies [9] and is highly sensitive to assumptions regarding their utilisation [10]. This challenge is particularly pronounced for emerging technologies, whose technical parameters are typically based on early-stage estimates

* Corresponding author.
E-mail address: jonathan.stelzer@kit.edu (J. Stelzer).

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that are difficult to validate and subject to considerable uncertainty. As a result, modelling outcomes can be strongly driven by assumed input parameters, potentially resulting in biased conclusions about their economic viability. Inverse methods can therefore be used to identify which combinations of techno-economic parameters would allow storage technologies to achieve economically viable investments [11].

At the same time, investors face uncertainties when considering emerging technologies, which significantly influence investment decisions [12]. In liberalised electricity markets, such risks are particularly relevant when revenues cannot be efficiently hedged through long-term contracts or futures markets [13], a situation described as missing market problem [14]. Storage revenues are primarily determined by electricity price spreads, which in turn depend on underlying market drivers [15]. Uncertainties in these drivers, such as renewable generation profiles [16] and short-term price dynamics [17], are inherently stochastic and often exhibit mean-reverting behaviour, fluctuating around a long-term equilibrium. Accounting for these uncertainties therefore seems important, as it could provide insights into which techno-economic storage configurations are robust and how they affect storage profitability and investment risk.

This study builds on a broad literature[1] assessing energy storage technologies from both cost-based and market-oriented perspectives. The LCOS has been widely applied to compare storage technologies such as lithium-ion batteries [18], redox flow batteries [10], and emerging systems like Carnot batteries [19]. However, these studies do not fully capture the interaction between technical design parameters, storage operation, and market conditions.

There are studies combine technical parameters with market-based revenue assessments. For instance, Spodniak et al. [20] investigate the impact of different Energy-to-Power (EtP) ratios on large-scale electricity storage in day-ahead markets across Germany, the UK, and Scandinavia. Komorowska et al. [21] analyse the financial performance of lithium-ion batteries, while Poli et al. [22] evaluate redox-flow batteries in European day-ahead markets. Cetegen et al. [23] evaluate liquid air energy storage under specific charge/discharge schedules in the Texas market, while Vecchi et al. [24] examine the additional revenue potential from reserve market participation. Similarly, Nitsch et al. [25] simulate battery storage operations in German day-ahead and frequency restoration markets using an agent-based electricity market model. Despite a more market-based modelling framework, these studies rely on predefined cost assumptions and focus on specific storage technologies. While such analyses can indicate whether a given technology may be economically viable under certain conditions, they provide limited insights into how storage systems should be designed or which techno-economic parameter combinations would enable profitability. To address this, recent studies apply inverse modelling approaches that directly link technical parameters to economic feasibility. Nitsch et al. [26] combine generation expansion and market modelling to evaluate the economic viability of Carnot batteries under decarbonised scenarios. Sorknæs et al. [27] assess their system cost reduction potential to determine their cost limits, while Stelzer et al. [28] analyse their profitability in the German electricity market for different EtP ratios and round-trip efficiencies (RTE). Together, these studies move toward linking technical design parameters with market competitiveness. However, they largely neglect the impact of investment risk and stochastic market conditions on storage profitability, leaving open the impact of uncertainty.

Studies that explicitly incorporate investment risk and uncertainty into storage valuation often move away from identifying maximum cost thresholds or applying inverse modelling approaches. Instead, they typically analyse predefined technology configurations under stochastic conditions. For instance, Geske et al. [29] apply a Markov decision model to optimise storage capacity under uncertain residual load, while Hammann et al. [30] adopt a real options framework to assess adiabatic compressed air energy storage under fuel price uncertainty. Similarly, Bakke et al. [31] analyse lithium-ion battery investments under uncertain spot and balancing prices, and Dimanchev et al. [32] develop an equilibrium generation expansion model capturing investors' risk exposure in incomplete markets and explicitly include storage in capacity expansion decisions.

Recent studies exhibit limitations similar to those discussed above. For instance, Friedel et al. [33] extend LCOS analyses across scenarios but do not incorporate explicit investment risk or detailed market dynamics. Poli et al. [22] consider techno-economic parameters under investment-related aspects, yet rely on simplified market representations. Mantegna et al. [34] and Esser et al. [11] analyse storage within capacity expansion frameworks, focusing on system design rather than investor risk exposure under uncertainty. Makrides et al. [35] model stochastic investment decisions, but do not derive implications for techno-economic design parameters. From this review, a clear gap emerges in linking technical design parameters for mid-term storage technologies with economic competitiveness under investment risk and market uncertainty.

The central hypothesis of this study is therefore whether mid-term storage configurations can effectively fill a mid-term segment in electricity markets while representing competitive and robust investment options. To investigate this question, this work adopts an inverse modelling perspective that explicitly links techno-economic design parameters with market-based revenues under stochastic future conditions. In contrast to existing studies that either focus on predefined technologies or analyse investment risk without deriving implications for technical design, this study explores a broad design space of mid-term storage configurations.

Against this background, this work aims at:

- identifying competitive mid-term storage configurations by analysing how combinations of RTE and EtP affect market viability and competitiveness,
- determining CAPEX for each configuration to assess economic feasibility and provide guidance on cost thresholds for emerging storage technologies,
- and evaluating the impact of uncertainties in key drivers on electricity price spreads, storage profitability, and risk for investors, to identify the mid-term storage options most robust under volatile market conditions.

To address these objectives, this study applies the agent-based power market model PowerACE[2] incorporating mean-reverting stochastic processes for fuel prices and renewable generation profiles. By simulating a range of future market conditions within 16 European countries, the model captures the impact of fundamental uncertainties on electricity price spreads. An inverse modelling approach is then used to explore combinations of RTE (10–100%) and EtP (8–168 h) for mid-term storage technologies, determining the maximum annualised CAPEX at which each configuration remains profitable. This metric is particularly useful because it allows storage configurations to be compared without specifying a discount rate or asset lifetime upfront. Once these values are known for a given technology, the corresponding annualised investment cost can be directly calculated and compared to the determined maximum CAPEX in this study.

The remainder of this paper is structured as follows. Section 2 outlines the methodological framework, including the stochastic price modelling and the assessment of profitability for mid-term energy storages under risk. Section 3 presents the main findings on price dynamics and storage profitability. Section 4 discusses the implications and limitations of the findings for technology design and investors, while Section 5 concludes.

[1] A more detailed and comprehensive literature review is provided in Appendix A.

[2] A description and overview can be found in Fraunholz [36].

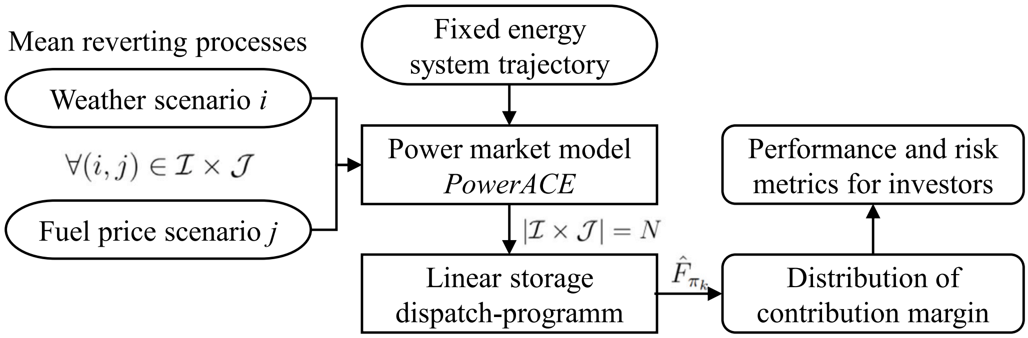


Fig. 1. Overview of the methodological process from data input to investment risk assessment.

2. Methods

To evaluate the performance and investment risk of mid-term storage technologies, uncertainty in the electricity system is explicitly considered. Variability in renewable generation and electricity demand profiles is represented by the set $\mathcal{I} = \{1, \dots, I\}$ of weather scenarios, each weighted according to its probability of occurrence, while fuel price uncertainty is represented by the set $\mathcal{J} = \{1, \dots, J\}$ of fuel price scenarios and modelled using an OU process to capture its mean reverting properties. The resulting $N = I \cdot J$ scenarios, combining weather scenario $i \in \mathcal{I}$ and fuel price path $j \in \mathcal{J}$ as scenario (i, j), serve as input for an agent-based power market model to generate N electricity price paths. In the model, a fixed energy system trajectory is assumed, i.e., there is no endogenous generation expansion or any structural change to the power plant fleet across scenarios. These price paths are subsequently used in a linear storage-dispatch program outside of the power market simulation. In this step, the storage operation is optimised with respect to the maximisation of the contribution margin[3] for each individual price path, determining the economically optimal charging and discharging schedule for the respective storage configuration. The resulting optimal dispatch decisions are then used to compute the distribution of contribution margins $\hat{F}_{\pi_k}$ for each parameter combination $k \in \mathcal{K} = 1, \dots, K$, providing a systematic risk assessment for investors and allowing the identification of storage configurations that remain economically robust under both weather and fuel price uncertainty. Based on these distributions, an inverse investment perspective is adopted: instead of assuming fixed CAPEX and evaluating profitability, the maximum annualised CAPEX that can still be covered by the stochastic contribution margins is determined for each parameter combination. This approach directly links technical design parameters to economically viable investments under uncertainty and enables a comparison of emerging storage concepts across a wide design space. The described methodological framework is illustrated in Fig. 1.

2.1. Probability of occurrence for weather scenarios

To account for uncertainties associated with the future patterns of generation and demand profiles, distinct weather scenarios are considered. A weather scenario represents a full year of data, including capacity factors for renewable generation and corresponding electricity demand profiles. To quantify the probability of occurrence for a given weather scenario $i \in \mathcal{I}$, a weighted aggregation approach is applied that accounts for spatial, technological and temporal heterogeneity. The probability weight w_i^w of scenario i is defined as:

$$w_i^w = \sum_{a=1}^{A} \sum_{c=1}^{C} \sum_{m=1}^{M} w_{a,c}^{\text{comp}} \cdot w_{a,c,m}^{\text{bin}} \tag{1}$$

where:

- $w_{a,c}^{\text{comp}}$ represents the relative share of contribution of component c in area a with respect to the total contribution across all areas. Here, c refers to the installed capacity of a renewable energy source or the total demand in area a.
- $w_{a,c,m}^{\text{bin}}$ denotes the fraction of weather scenarios in area a, for component c and month m that fall within a predefined bin. The bins are defined based on the standard deviation of the corresponding time series of a component. Specifically, for each month, the mean of the time series (e.g., hourly capacity factors) is calculated for each scenario. Then, the overall mean across all scenarios for that month is determined. The deviation of each scenario's monthly mean from the overall monthly mean is computed and assigned to a bin, such that all scenarios within the same bin are assigned the same probability. Bins are defined such that the probability of each bin is given by the fraction of scenarios that fall within it. Deviations are categorised into bins corresponding to the ranges between $-2, -1, 0, 1, 2$ standard deviations, with any values below or above these limits assigned to the outermost bins.

By summing over all areas, components, and months, a weight for each weather scenario for a given year is obtained. A more detailed mathematical formulation of the approach can be found in Appendix C.2.

2.2. Modelling of fuel price trajectories

The modelling of fuel prices often requires stochastic processes. A widely applied framework is the OU process,[4] which is defined by the stochastic differential equation

$$dX_t = \theta(\mu - X_t)\, dt + \sigma\, dW_t \tag{2}$$

where μ denotes the long-term equilibrium level, θ is the speed of mean reversion, σ the volatility parameter, and W_t a standard Wiener process [41]. Here, t represents time steps, corresponding to the daily fuel prices. The process is particularly suitable for commodities in energy markets, since empirical price dynamics often revert to a long-term average while still exhibiting short-term noise [42]. To account for the dependence of fuel prices, correlations are introduced using a Cholesky decomposition of the empirical covariance matrix. The

[3] The contribution margin corresponds to the net operating profit, calculated as the revenues from discharged electricity, minus the cost of electricity purchased for charging, accounting for round-trip efficiency and operational constraints. Capital expenditures are excluded at this stage.

[4] Examples can be found in [37–39], and [40].

univariate process in Eq. (2) is then extended to a multivariate process, after discretisation:

$$X_{t+\Delta t} = X_t + \theta \cdot (\mu - X_t)\,\Delta t + Lz\sqrt{\Delta t}, \tag{3}$$

where z is a vector of standard normal draws and L is the lower-triangular matrix obtained from the Cholesky decomposition of the empirical covariance matrix Σ, such that $\Sigma = LL^{\top}$.

To adequately capture the effects of fuel price uncertainty on storage performance, it is necessary to consider a large number of simulated price trajectories. To incorporate a large set of trajectories directly into the analysis would, however, be computationally prohibitive. Therefore, a clustering procedure is applied to reduce the dataset. First, the simulated paths are reduced to their two principal components via principal component analysis. Subsequently, the resulting components are grouped into clusters using K-Means clustering. For each cluster, the time series closest to the cluster centroid (i.e., minimising the Euclidean distance) is selected as the representative fuel price path, denoted by $j \in \mathcal{J}$, and assigned a weight w_j^f proportional to the fraction of total paths contained in that cluster.

2.3. Linear storage dispatch-program

A commonly studied application of energy storage is electricity price arbitrage, where electricity is purchased at low prices and sold at higher prices. Assuming that the storage system is small enough that its charging and discharging do not affect market prices, analyses of this price-taker scenario often assume perfect optimisation of the device when faced with known electricity prices.

The simulated wholesale electricity price paths obtained from the agent-based power market model are used as input for such a simplified storage dispatch optimisation problem, with the objective of maximising the contribution margin given the technical design parameters such as storage capacity, charging and discharging power, and RTE.

Let T denote the number of time steps in the considered price path. The decision variables are the charging power P_t^{ch}, discharging power P_t^{dis}, and state-of-charge SOC_t at each time step $t \in \{1, \dots, T\}$.

The optimisation problem is formulated as follows:

$$\max_{P_t^{\mathrm{ch}}, P_t^{\mathrm{dis}}, SOC_t} \quad \sum_{t=1}^{T} \left(-P_t^{\mathrm{ch}} \cdot p_t + P_t^{\mathrm{dis}} \cdot p_t\right) \tag{4}$$

$$\text{s.t.} \quad SOC_{t+1} = SOC_t + \eta^{\mathrm{ch}} P_t^{\mathrm{ch}} - \frac{1}{\eta^{\mathrm{dis}}} P_t^{\mathrm{dis}} \quad \forall t = 1, \dots, T-1 \tag{5}$$

$$0 \le SOC_t \le C \quad \forall t = 1, \dots, T \tag{6}$$

$$0 \le P_t^{\mathrm{ch}} \le P^{\mathrm{ch,max}} \quad \forall t = 1, \dots, T \tag{7}$$

$$0 \le P_t^{\mathrm{dis}} \le P^{\mathrm{dis,max}} \quad \forall t = 1, \dots, T \tag{8}$$

$$SOC_1 = 0 \tag{9}$$

Here, p_t denotes the simulated electricity price at time t, C is the storage capacity, $P^{\mathrm{ch,max}}$ and $P^{\mathrm{dis,max}}$ are the maximum charging and discharging powers, and η^{ch} and η^{dis} are the charging and discharging efficiencies. The initial state-of-charge is set to 50% of the storage capacity, with self-discharge as well as variable operation and maintenance costs neglected. Battery degradation, while relevant for certain storage technologies, is not explicitly modelled due to the technology-neutral scope of the analysis and the associated modelling complexity.

The objective value of the optimisation can be interpreted as the annual contribution margin per MW generated by the storage in a given year, which can be used to cover the equivalent annualised investment and fixed operation and maintenance costs. Conducted independently of the power market model, this approach facilitates the systematic evaluation of diverse system configurations and allows for the adjustment of key parameters, such as the EtP ratio, while simultaneously determining the maximum CAPEX that ensures economically viable operation for a given RTE and capacity.

2.4. Performance and risk metrics for investors

Investment decisions under uncertainty can be evaluated using the empirical distribution of profitability across different scenarios. In the context of this study, each simulated electricity price path is assigned a weight corresponding to its probability $w_{i,j}^p$, defined as the product of the weight of the weather scenario w_i^w and the fuel price trajectory w_j^f, which in turn induces a probability distribution for the annual contribution margin, derived in Section 2.3, which determines the maximum economically viable CAPEX. According to [12], the empirical distribution function and the corresponding empirical cumulative distribution function of the contribution margin for a given storage configuration can then be used to derive various decision metrics, allowing consideration of both expected profitability and risk exposure.

Formally, let $\pi_{k,(i,j)}$ denote the contribution margin of parameter combination $k \in \mathcal{K}$ under the price path scenario defined by weather year i and fuel price path j, with associated scenario probability $w_{i,j}^p$. The expected contribution margin $\mathbb{E}(\pi_k)$ of a parameter combination k is then defined as the weighted average over all scenarios:

$$\mathbb{E}(\pi_k) = \sum_i \sum_j w_{i,j}^p \, \pi_{k,(i,j)}. \tag{10}$$

To account for risk aversion in investment decisions, risk measures are applied to the empirical distribution $\hat{F}_{\pi_k}$. Based on the empirical cumulative distribution function, a well-established and widely used risk measure is the value at risk (VaR_α), which indicates the threshold of the contribution margin that will be achieved or exceeded with a given confidence level. Specifically, the VaR_α at confidence level α is given by

$$\mathrm{VaR}_\alpha(\pi_k) = \max\left\{ q \,:\, \Pr\left(\pi_{k,(i,j)} < q\right) \le 1 - \alpha \right\}, \quad \forall \alpha \in (0,1) \tag{11}$$

and the conditional value at risk (CVaR_α), which is a coherent and widely used risk measure, is defined as the contribution margin conditional on falling below the VaR_α:

$$\mathrm{CVaR}_\alpha(\pi_k) = \mathbb{E}\left[\pi_{k,(i,j)} \mid \pi_{k,(i,j)} \le \mathrm{VaR}_\alpha(\pi_k)\right], \quad \forall \alpha \in (0,1). \tag{12}$$

To jointly account for expected profitability and risk, a linear combination of the expected value and the CVaR is applied, following the approach of Fraunholz et al. [12]:

$$\pi_k^* = (1-\lambda)\,\mathbb{E}(\pi_k) + \lambda\,\mathrm{CVaR}_\alpha(\pi_k), \quad \lambda \in [0,1],\ \alpha \in (0,1), \tag{13}$$

where λ represents the investor's degree of risk aversion, with $\lambda = 0$ corresponding to risk-neutral and $\lambda = 1$ to highly risk-averse preferences. Following this approach, π_k^* provides a single metric that quantifies the maximum contribution margin achievable for each storage parameter combination, and therefore the maximum CAPEX under which economically viable operation is maintained. To determine the relative competitiveness of each storage configuration compared to another, the deviation of the maximum annualised CAPEX is calculated as

$$\Delta\pi_k^{\mathrm{ref}} = \pi_k^* - \pi^{\mathrm{ref}} \tag{14}$$

where π^{ref} denotes the maximum annualised CAPEX of the reference configuration for the same λ. A positive value of $\Delta\pi_k^{\mathrm{ref}}$ indicates that configuration k can sustain higher annualised CAPEX than the reference system while maintaining economic viability, whereas a negative value indicates lower allowable CAPEX. Additionally, for $\lambda = 0$ and $\lambda = 1$, the percentage change of the maximum annualised CAPEX can be expressed as

$$\Delta\pi_k^{\mathrm{risk}} = \frac{\pi_k^*(\lambda = 0) - \pi_k^*(\lambda = 1)}{\pi_k^*(\lambda = 0)} \times 100\%, \tag{15}$$

where

$\pi_k^*(\lambda = 0) = \mathbb{E}(\pi_k),$

$\pi_k^*(\lambda = 1) = \mathrm{CVaR}_\alpha(\pi_k),$

which can be interpreted as the risk premium of a highly risk-averse investor relative to a risk-neutral investor.

Eqs. (13)–(15) quantify the economic competitiveness and impact of risk preferences on the maximum achievable contribution margin and the corresponding maximum annualised CAPEX for each storage configuration, taking into account both expected performance and downside risk.

2.5. Data, assumptions, and market modelling

To identify economically viable and robust mid-term storage investment options under varying future market conditions, the following data sources and assumptions are applied.

A total of 36 distinct weather scenarios are taken from the European Resource Adequacy Assessment (ERAA) Executive Report 2024 [43], providing hourly datasets for renewable generation and demand profiles under varying future weather and climate conditions. For all other system components, the same values from the fixed energy pathway trajectory presented in Appendix B.1 are used. The resulting weather scenario weights are provided in Appendix B.2.

Fuel prices are simulated following the Ten-Year Network Development Plan (TYNDP) scenarios over the period 2030–2050. Initial values X_0 for 2030 are taken from the TYNDP 2024 [44], while the long-term mean μ is set according to projected 2050 fuel and CO_2 prices. The mean-reversion speed θ and volatility σ of the multivariate OU process are estimated from historical front-month price data from 2023–2024 using a discrete-time approximation [45]. Specifically, an autoregressive regression of order one is applied to observed price differences, with the slope providing $-\theta\Delta t$ and the standard deviation of residuals yielding σ. Gas, oil, and hard coal are explicitly considered, while hydrogen is included under the assumption that its price dynamics follow natural gas, reflecting the expected linkage of emerging hydrogen markets to gas price developments [46]. Carbon prices are modelled jointly with fossil fuels, combining the corresponding emission factors [44] with CO_2 prices to include carbon costs directly in the fuel time series. The parameters X_0, μ, θ, σ, and the empirical covariance matrix are provided in Appendix B.3. A total of 1000 fuel price paths are simulated to capture a wide range of uncertainty. To reduce computational complexity, the trajectories are clustered using a two-step procedure: first, principal component analysis reduces each path to its two principal components, and then K-Means clustering groups these components into ten clusters. The resulting ten representative paths and their weights are presented in Appendix B.4. All prices are reported in nominal € using inflation rates from the World Economic Outlook 2024 [47].

Finally, the weather scenarios and representative fuel price paths are combined to simulate electricity price paths for the years 2035, 2040, and 2045, which serve as the basis for the storage profitability analysis.

The simulations of electricity price paths are carried out using the agent-based power market model PowerACE. PowerACE is a simulation framework based on individual market participants, designed for the analysis of European electricity markets. Its primary purpose is to enable long-term assessments of the day-ahead market. Depending on the input data resolution, the model simulates 8760 h of a year across extended time horizons. Over the past years, PowerACE has been applied in a variety of research contexts, such as studies about electricity prices [48], capacity remuneration mechanisms [49], the analysis of electric vehicle market impacts [50] and for assessing the role of risk aversion in capacity expansion planning [12].

Within the model, market participants are equipped with internal decision-making strategies that define their individual objectives, such as the maximisation of profits. These participants continuously interact with their environment and, on each simulated day, submit demand or supply bids according to their respective strategies. The day-ahead market outcome is then determined by a welfare-maximising market-clearing algorithm, which accounts for all submitted bids as well as the available cross-border transmission capacities. A comprehensive and authoritative description of the structure and individual modules of the PowerACE model can be found in [36]. Fig. 2 provides a simplified representation of the modelling approach used in this study.

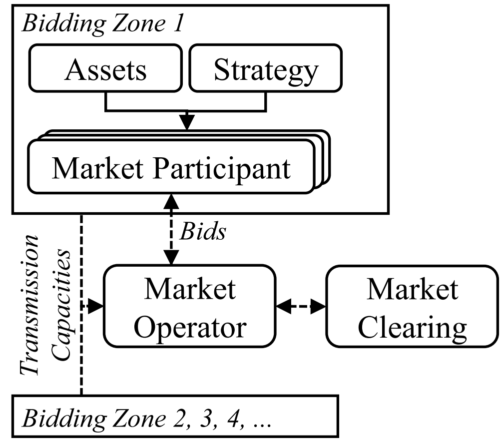


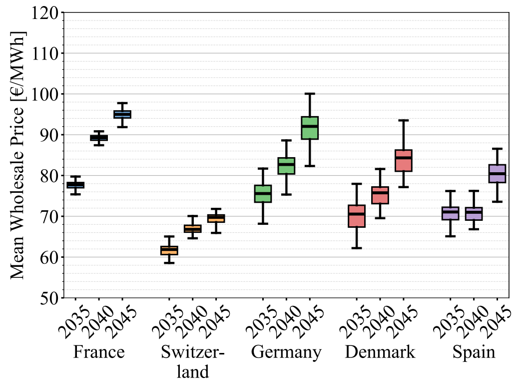
Fig. 2. Simplified overview of the power market model PowerACE.

Consistent with the assumptions above, the energy system trajectory of the TYNDP 2024 Global Ambition Scenario is applied. In the energy system trajectory, the installed capacity is expanded by additional gas turbine power plants to fulfil the required system reliability in each bidding zone. By assuming a fixed energy pathway, the variability in weather years and fuel prices allows for representing the uncertainties in these underlying mean reverting processes for future day-ahead electricity price developments. The simulations cover 16 bidding zones, each with its respective day-ahead wholesale market prices. By combining ten representative fuel price trajectories with 36 weather scenarios, a total of $N = 360$ day-ahead price paths are generated for each year and each bidding zone.

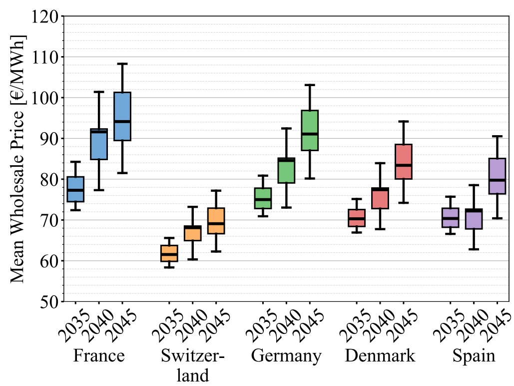
The linear dispatch problem is then solved sequentially across multiple price paths, but simultaneously for different storage parameter combinations, with a warm-start procedure applied to accelerate convergence across price paths. In this study, the discharge and charge powers are fixed to 1 MW, efficiencies are varied from 10% to 100% in 1-percentage-point increments, and 168 different storage capacities are considered, resulting in a total of $91 \cdot 168 \cdot 360 = 5,503,680$ linear program evaluations for a single bidding zone and year with $T = 8760$. Using this approach, solving the optimisation for all scenarios for one year and bidding zone takes on average approximately 440 min on an AMD Ryzen Threadripper 3970X 32-core processor using the simplex algorithm.

3. Results

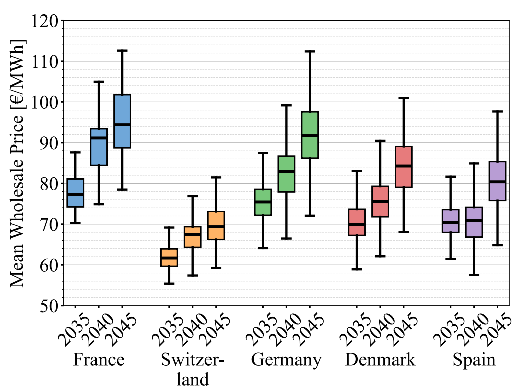
The results build on the data and assumptions described in Section 2.5, which capture uncertainties in renewable generation, fuel prices, and electricity demand. In the following, the results are presented in three stages: wholesale prices and spreads, storage competitiveness, and investor risk preferences.



(a) Distribution across varying weather scenarios, with fuel price scenarios averaged per weather scenario.



(b) Distribution across varying fuel price scenarios, with weather scenarios averaged per fuel price scenario.



(c) Distribution across all weather and fuel price scenarios.

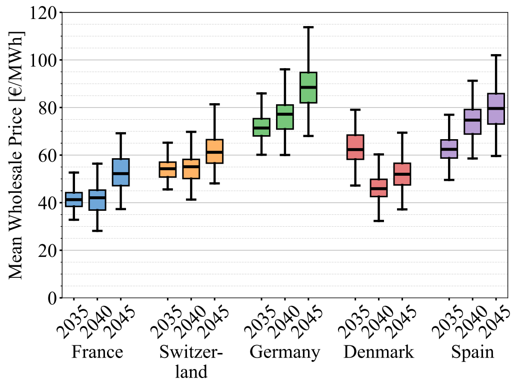
Fig. 3. Boxplots of mean wholesale prices across scenarios for different European countries.

3.1. Comparison of electricity price paths

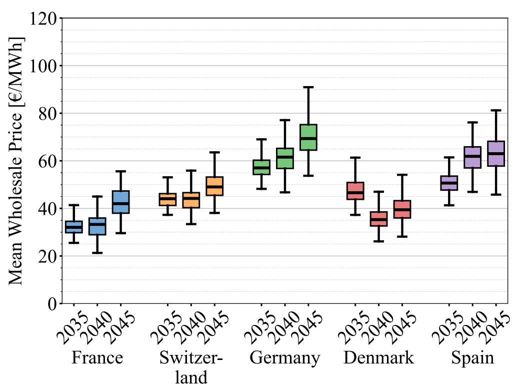
In Fig. 3(a), the distribution of mean prices is shown for the years 2035, 2040, and 2045[5] across different European countries under varying weather scenarios, i.e. wind and solar generation profiles. Fig. 3(b) illustrates the corresponding distributions under varying fuel price assumptions.[6] The scenarios capture structurally diverse energy systems: Germany is characterised by high renewable penetration combined with increasing demand, France remains strongly reliant on nuclear power, Denmark is dominated by wind generation, Spain benefits from abundant solar resources, and Switzerland reflects its characteristic hydro-based system, while also being strongly influenced by neighbouring countries. The comparison between weather-year and fuel price scenarios reveals distinct sensitivities across the analysed countries. Due to its reliance on nuclear power, France shows only minor variation across different weather years, but is strongly affected by changes in fuel prices. Switzerland exhibits a similar pattern: weather-year variations have little impact, while fuel price assumptions significantly influence the mean price distribution. In Germany, fuel price assumptions dominate the distribution of mean prices, reflecting the role of flexible thermal generation (e.g., gas turbines or hydrogen-based plants), while variations across weather years also have a significant impact. Denmark has a large wind generation capacity, which allows it to cover a substantial share of its electricity demand from domestic wind resources. However, its system is strongly influenced by Germany,

[5] The exogenous energy system trajectory and the corresponding demand for each year can be found in Appendix B.1.

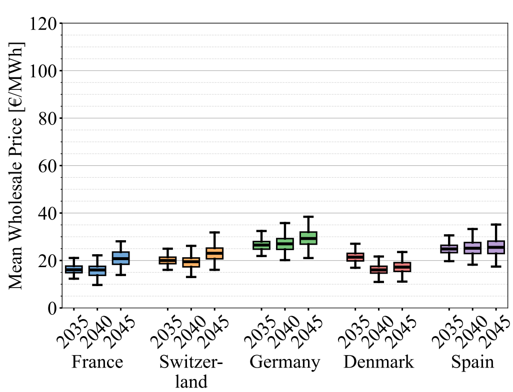
[6] The fuel price scenarios and their variability can be found in Appendix B.4.



(a) Distribution of the daily mean of the second-highest spread.



(b) Distribution of the daily mean of the fourth-highest spread.



(c) Distribution of the daily mean of the eighth-highest spread.

Fig. 4. Boxplots of the daily mean of the second-, fourth-, and eighth-highest wholesale price spreads across scenarios for different European countries.

resulting in similar sensitivities to changing conditions. In Spain's solar-dominated system, solar variability has a relatively minor effect on the price distribution, whereas fluctuations in fuel prices of flexible thermal power plants drive changes in mean values. Fig. 3(c) presents the distribution of mean prices when both weather year and fuel price variations are considered simultaneously. The combination of these two sources of uncertainty introduces differences in all analysed countries. Comparing across years, it becomes apparent that the variance of the mean price distributions tends to increase in 2040 and 2045. The impact of fuel price variations is relatively high compared to weather scenario variations, as the mean prices diverge further due to the dynamics of the OU process (cf. Appendix B.4). Moreover, in systems where weather scenario variations have a significant impact (e.g., Germany), the overall spread of mean price distributions becomes notably larger compared to countries where weather sensitivity is low (e.g., France). Consequently, the combination of sensitivity to both weather scenarios and fuel price variations drives the overall variation to the greatest extent.

Negative wholesale price events occur only rarely in the analysed scenarios. The large-scale deployment of storage and electrolyser capacities utilises surplus renewable generation, effectively limiting extreme price drops and reducing the frequency of negative prices. As a result, storage profitability is driven less by extreme negative price events and more by the magnitude and consistency of positive price spreads. Accordingly, Fig. 4 presents the distribution of the averages of the second-, fourth-, and eighth-highest daily price spreads.[7] As the fourth-highest daily spread remains relatively close to the second-highest, an increase in storage capacity could be beneficial within this range. In contrast, the eighth-highest spread is considerably lower, implying that increasing capacity or using low-efficiency storage would yield only limited contribution margins when exploiting these spreads. Comparing countries, price spreads are consistently highest in Germany, indicating favourable conditions for storage profitability. Spain also exhibits relatively large spreads, suggesting similarly favourable opportunities. In contrast, France, dominated by nuclear generation, and Denmark, with a high share of wind power, exhibit lower spreads, implying less attractive conditions for storage deployment. The absolute variation in average spreads across different fuel price and weather scenarios is highest for the 2-hour spreads, while it decreases for the 8-hour spreads (cf. Germany 2045: 49.21 €/MWh vs. 19.05 €/MWh). Accordingly, the potential exploitation of these spreads by storage systems results in more consistent contribution margins between scenarios.

3.2. Competitiveness of different storage parameter combinations

In the following subsections, when referring to a risk-neutral or risk-averse investor, the contribution margin π^*, as defined in Eq. (13), is considered. A risk-neutral investor corresponds to $\lambda = 0$, while a risk-averse investor corresponds to $\lambda = 1$. Accordingly, for a risk-neutral investor, the figures depict the expected value of the contribution margin, whereas for a risk-averse investor, the CVaR_α of the contribution margin is shown. The maximum annualised CAPEX shown in the following subsections is assumed to equal the contribution margin π^*_k for a year that can be achieved with the respective combination of storage parameters k. Since the values represent the maximum allowable annualised costs to ensure profitability, any fixed operation and maintenance costs, if considered, would need to be deducted accordingly to obtain the maximum admissible CAPEX.

As described in Section 2.3, discharge and charge powers are fixed to 1 MW, while storage capacities are varied between 1 MWh and 168 MWh. The round-trip efficiency (RTE) is modelled via input efficiency, such that all storage capacities are expressed in electrical terms. Accordingly, the storage capacity can be described by the Energy-to-Power (EtP) ratio, which denotes the discharge duration, i.e., the time a storage system can continuously release energy at its rated power from full charge to full discharge in hours.

Fig. 5 shows the maximum annualised CAPEX π^* for Germany in 2035 required to achieve an annuity of zero, as a function of EtP ratio and RTE, assuming a risk-neutral investor. The contour lines in Fig. 5 represent equal maximum annualised CAPEX values, which allow to identify combinations of EtP ratio and RTE that are economically equivalent. For example, a technology with lower RTE can achieve comparable economic performance if the EtP ratio is sufficiently increased. It can be observed that, particularly for low EtP ratios, an increase in RTE yields comparatively little economic benefit, as lines of equal maximum annualised CAPEX are predominantly vertical in this region. In contrast, an increase in EtP ratio proves to be more

[7] The calculation of daily spreads is detailed in Appendix C.1.

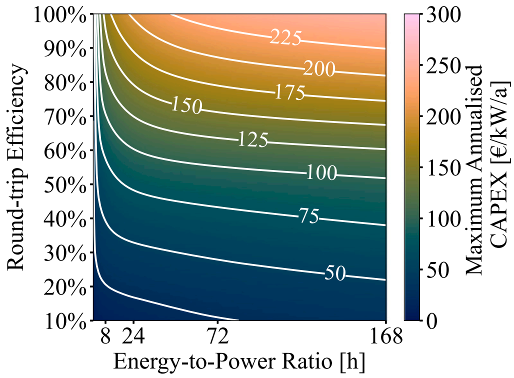


Fig. 5. Maximum annualised CAPEX π^* (cf. Eq. (13)) in Germany (2035) for a risk-neutral investor ($\lambda = 0$).

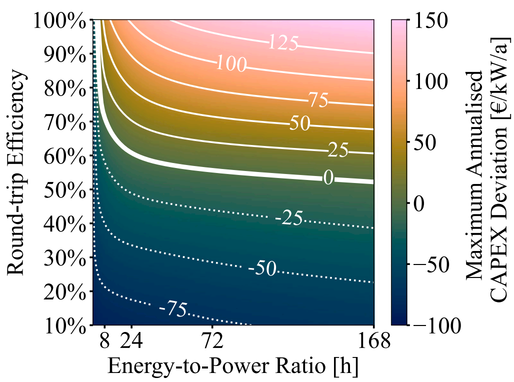


Fig. 6. Maximum annualised CAPEX deviation $\Delta\pi_k^{\text{ref}}$ according to Eq. (14) for $\lambda = 0$ in Germany (2035) required to achieve the same annuity relative to a 4 hour EtP ratio and 92% RTE storage system with a contribution margin π^{ref} of 101.04 €/kW/a.

advantageous. With higher EtP ratios, this pattern changes: the contour lines shift toward a more horizontal orientation. Consequently, further increases in the EtP ratio become less beneficial, while improvements in RTE gain relative importance. From this, it becomes evident that the marginal value of additional capacity declines rapidly and remains at low levels from around 8 h of storage duration onward, depending on the RTE, as this turning point appears to shift to higher EtP ratios as RTE increases. The same qualitative observations apply to the years 2040 and 2045, as well as to the other analysed countries. While the absolute levels of the maximum annualised CAPEX differ due to variations in price spreads across different years and countries, the qualitative relationships between EtP ratio and RTE remain unchanged. The corresponding figures are provided in Appendices B.5 and B.6[8]

Fig. 6 shows a similar graph for Germany in 2035 for a risk-neutral investor. The maximum annualised CAPEX deviation $\Delta\pi_k^{\text{ref}}$ is shown relative storage system representing a lithium-ion battery. The resulting deviation shows how much more or less annualised CAPEX is allowed for each storage configuration compared to the lithium-ion battery to achieve the same annuity. Therefore, the contour along the zero line represents combinations of parameters that yield the same annuity as the reference lithium-ion battery, if the annualised CAPEX between them are equal. It can similarly be inferred that higher (lower) techno-economic parameters allow for correspondingly greater (smaller) CAPEX deviations to be competitive. This relationship

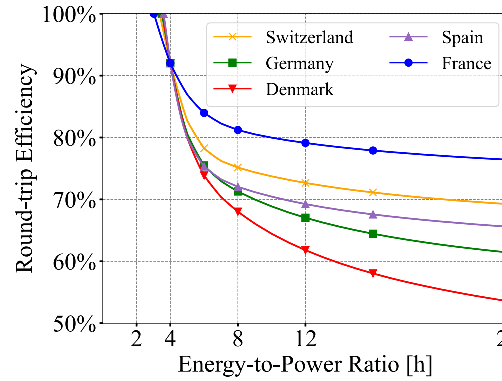


Fig. 7. Extracted zero-contour lines (cf. Fig. 6) for different countries averaged over the years 2035, 2040, 2045, showing combinations of RTE and EtP that yield the same annuity as the reference 4 h lithium-ion battery system.

exhibits the same quantitative trend as the maximum allowable CAPEX shown in Fig. 5.

For Fig. 7, contours along the zero line are extracted for different countries. At a low EtP ratio, the curves show little variation. They decline sharply, meaning that an increase in the EtP ratio allows for a large reduction in RTE while maintaining the same profitability. The differences emerge at the points where the curves transition from a rather vertical to a more horizontal profile. This occurs at different RTE values. For EtP ratios up to 8 h, increasing the EtP ratio can still allow substantial reductions in RTE, averaging 18% across all countries when moving from a 4 h to an 8 h EtP ratio. In most countries and years, these benefits level off around this point. Beyond 8 h, further increases in the EtP ratio yield diminishing gains, averaging 8% across all countries when moving from an 8 h to a 24 h EtP ratio. However, in some cases, such as Germany, appreciable reductions persist for EtP ratios up to 24 h. Notably, the location of this transition varies across countries and years: in the cases of Switzerland and France, the transition starts for higher RTE, resulting in a more rapid diminishing benefit of higher EtP ratios, while in Germany, Spain, and Denmark, the transition starts at a lower RTE, indicating that lower a RTE benefits from higher EtP ratios for competitiveness. The comparison of this reference lithium-ion system indicates that competitiveness can be maintained even at lower efficiencies, provided that the EtP ratio is sufficiently high. As can be inferred from Fig. 5, this observation can be generalised to energy storage technologies more broadly, suggesting that economic competitiveness at lower efficiencies can be achieved through a higher EtP ratio. However, this requires that the marginal costs of additional capacity remain low enough to keep the overall CAPEX at a level comparable to the lithium-ion reference. At the same time, total CAPEX must be low enough to ensure that the achievable contribution margin still results in a profitable investment.

3.3. Investor risks

Fig. 8 shows the percentage deviation in maximum allowed CAPEX between a risk-neutral and a risk-averse investor in Germany for 2035, calculated as $\Delta\pi_k^{\text{risk}}$, with risk aversion incorporated via CVaR_α at $\alpha = 95\%$. The percentage change can be interpreted as the risk premium of a highly risk-averse investor relative to a risk-neutral investor. It can be observed that for higher RTE values, an initial increase in the EtP ratio can still reduce risk, but the effect diminishes as the EtP ratio continues to rise. For values around 50% RTE, the effect is already relatively flat from the beginning, whereas for lower RTE values, an initial increase in the EtP ratio reduces risk at first, but later on the risk starts to increase again. By varying the RTE, it can be observed that for lower EtP ratios, the effect on the risk premium is rather inconsistent.

[8] Additional sensitivity analyses were conducted for an alternative system pathway B.7, for variations in charge and discharge power B.8, as well as for variable operation and maintenance costs and self-discharge B.9.

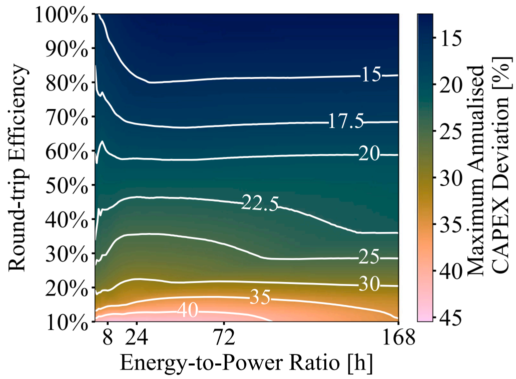


Fig. 8. Percentage change in maximum annualised CAPEX $\Delta\pi_k^{\mathrm{risk}}$ (cf. Eq. (15)) for a risk-averse investor ($\lambda = 1$) relative to a risk-neutral investor ($\lambda = 0$) for Germany in 2035.

However, for higher EtP ratios, it becomes evident that an increase in RTE leads to the strongest reduction in the risk premium, especially when compared to the influence of the EtP ratio itself.

Fig. 9(a) illustrates the change in the risk premium $\Delta\pi_k^{\mathrm{risk}}$ with increasing RTE, averaged over all years for each country and across all EtP ratios corresponding to that RTE. It can be observed that, for all countries except France, the risk premium decreases as RTE increases, although the rate of decrease varies between countries. Fig. 9(b) shows a similar analysis, but with increasing EtP ratio. Here, notable differences between countries emerge: while Germany exhibits hardly any effect, France experiences a substantial decrease in the risk premium as EtP increases. In contrast, Denmark's risk premium increases with higher EtP ratios. For risk-averse investors, higher RTE can thus be desirable. Although the magnitude of this effect clearly depends on the country-specific market conditions, it can reduce the risk premium in some cases, making investments relatively less risky. Consequently, technologies that achieve elevated RTE may be particularly attractive to conservative investors, as they mitigate perceived uncertainties and stabilise expected returns.

4. Discussion

The primary contribution of this paper lies in assessing mid-term storage profitability from an investor's perspective, while simultaneously providing valuable insights for the design of these technologies. In particular, the findings highlight which technical characteristics are most critical for achieving stable revenues under uncertain future market conditions. This, in turn, provides an important foundation for developing storage technologies that can offer economically viable investment options and align technical design choices with the requirements of future electricity markets.

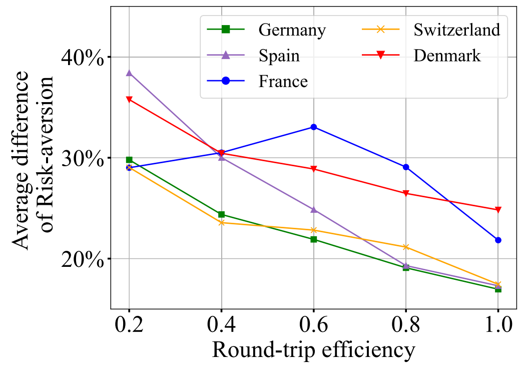
4.1. Implications for the design of emerging storage technologies

One of the central findings of this work concerns the role of emerging storage technologies in bridging the mid-term storage gap between short-duration and seasonal storage systems. Whether this mid-term segment can be effectively established is primarily determined by the cost of adding additional storage capacity. As shown in Fig. 5, for increasing EtP ratios beyond 24 h, the contour lines exhibit an almost constant slope. This indicates minor changes of the maximum CAPEX for a given efficiency with increasing EtP ratios, as the marginal contribution margin decreases rapidly with increasing storage capacity, a finding, which is in line with [20]. On the other hand, for a constant EtP ratio, increasing RTE leads to significant improvements in maximum allowable CAPEX, demonstrating how improvements in RTE strongly enhance the economic margin for storage technologies, aligning with the findings of Sioshansi et al. [51]. This implies that if seasonal storage technologies are already economically viable considering their total CAPEX, they will remain profitable in the mid-term range. For short-duration technologies, however, CAPEX levels must already be sufficiently low to realise economically viable systems. If the marginal cost per additional unit of capacity is too high, these technologies cannot profitably extend into the mid-term range. Hence, the emergence of a mid-term storage segment in the market is less subject to the EtP ratio itself, but a function of cost structure. The CAPEX characteristics of technologies aimed at serving this segment must enable them to outperform short-duration storage systems at higher storage durations while remaining competitive against seasonal solutions. This outperforming effect, where total CAPEX of mid-term systems becomes lower than that of short-duration systems, must occur at sufficiently small capacities to prevent seasonal storage from dominating the same range through more favourable cost scaling. For technology development and design, this implies that minimising costs per unit of capacity should be a key design objective, as it enables the technology to reach economically viable operation at relatively low EtP ratios. Fig. 6 further illustrates that technologies with lower RTE can match the performance of lithium-ion batteries by increasing their EtP ratio, but this requires careful optimisation of component sizing and material utilisation to keep the specific costs per unit of energy low. The RTE represents an additional design lever, highlighting the importance of improving conversion efficiency to enhance the overall competitiveness of mid-term storage technologies compared to short- and long-duration systems.

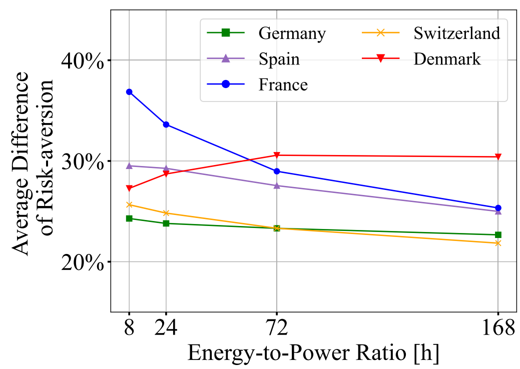
In summary, these findings highlight the role of technical design choices in determining the competitiveness and investment feasibility of mid-term storage technologies, reflecting the core aims of this research.

Further analyses of energy storage systems with capacity expansion models [52] confirm that energy capacity costs and round-trip efficiency are the dominant factors determining economic performance. These findings support the generality of the design implications, emphasising that minimising energy CAPEX and improving RTE are key levers for profitable mid-term storage under varying market conditions. Enhancing these design aspects can thus enable the design of storage technologies to offer attractive and competitive incentives for investors. At the same time, the relevance of these design implications depends on the underlying modelling approach, its methodological assumptions and market context. For instance, Esser et al. [11] report contrasting results based on a capacity expansion model, suggesting different design priorities for emerging storage technologies. For the example of Carnot batteries,[9] they find that an increase in the EtP ratio more efficiently increases the maximum allowable CAPEX than the RTE. Thus, for the design of emerging technologies, they suggest favouring an increase in the EtP ratio over the RTE. Theoretically, the profit maximisation objective of individual agents applied in this study aligns with the cost minimisation objective of a central planner in an idealised market, as used by Esser et al.. First, this study assumes exogenously given capacities, whereas Esser et al. consider endogenous capacity expansion. In this study, storage operates within an existing system configuration and exploits given price spreads without influencing them. As a consequence, increasing the EtP ratio expands operation to only a limited number of additional hours, which exhibit smaller and less pronounced price spreads. The additional contribution margin therefore declines, implying that the total contribution margin does not increase proportionally with a higher EtP ratio. This effect is not specific to the present model but is also captured in capacity expansion models, where contribution margins are endogenously determined as

[9] Carnot battery also is referred to as pumped heat energy storage or, less specifically, power-to-heat-to-power energy storage.



(a) Average change in the risk premium with increasing RTE for each country, averaged over all years and all EtP ratios corresponding to that RTE.



(b) Average change in the risk premium with increasing EtP ratio for each country, averaged over all years and across all RTE values corresponding to that EtP.

Fig. 9. Average risk premium change $\Delta\pi_k^{\mathrm{risk}}$ (cf. Eq. (15)) for a risk-averse investor ($\lambda = 1$) relative to a risk-neutral investor ($\lambda = 0$). Lower values indicate a smaller difference between a risk-averse and risk-neutral investor, reflecting more robust contribution margins.

a function of capacity expansion decisions. In contrast, an increase in RTE can unlock additional arbitrage opportunities by reducing per-cycle losses, thereby enabling the utilisation of smaller price spreads that would otherwise be unprofitable. Second, in a capacity expansion model with endogenous investment decisions, scarcity prices emerge as equilibrium outcomes reflecting system adequacy constraints. These scarcity rents, which would otherwise be captured by firm capacity, can instead be appropriated by cost-competitive storage technologies with high EtP, potentially displacing conventional firm capacity as a profitable investment option. In such idealised settings, scarcity prices are typically not subject to explicit upper bounds. In principle, a single extreme scarcity hour with very high prices could therefore be sufficient to render an investment profitable. In contrast, most real-world energy-only markets impose price caps, limiting the magnitude of scarcity rents. Under these conditions, several scarcity hours are generally required for the marginal unit to recover its fixed costs, or additional remuneration mechanisms, such as capacity markets, must provide complementary investment incentives to ensure resource adequacy.

For technology design, it is essential to consider both modelling perspectives in order to support robust technology development and to effectively guide design strategies for emerging storage technologies. In particular, designing storage technologies should account for two key requirements. First, designs must address system-level needs from a central-planner perspective, ensuring adequate energy provision, for example through higher EtP ratios. Second, technologies must also be economically viable from an individual view, meaning that storage systems should exhibit performance characteristics that support positive investment returns in the underlying market context. Such economic viability can be assessed in both capacity expansion models and agent-based models. In this work, the chosen approach offers complementary advantages, as it is more computationally tractable and allows for the analysis of a larger number of scenarios and sensitivities. Moreover, the use of an exogenous capacity mix enables the representation of out-of-equilibrium conditions and provides insights into short- to medium-term market outcomes before or after the system adjusts through investment.

4.2. Implications for investors

Based on the implications for technology design, several conclusions can be drawn for potential investors. Given Table 1, which presents the annualised CAPEX for various storage technologies, it becomes evident that the maximum CAPEX required to reach economic break-even, as illustrated in Figs. 5, lies far below the investment levels associated with storage technologies indicated in the Danish Energy Agency Technology Data Report [53] and Dumont et al. [54]. I.e., the marginal cost of additional capacity exceeds the marginal contribution margin attainable through market operations, implying that further capacity expansion does not yield a positive annuity. Moreover, as shown in Table 1, lithium-ion batteries[10] become more expensive in annuity terms than alternative technologies beyond a certain EtP threshold. However, at these thresholds, the marginal contribution margins are

[10] Under the assumptions underlying the results in Table 1, lithium-ion batteries would not constitute a profitable investment. This contrasts with their current (2025) high attractiveness and grid-connection requests in Germany, which is largely driven by revenues from multiple value streams across different markets, whereas this analysis considers arbitrage income from a single wholesale market only.

Table 1
Maximum annualised CAPEX for Germany in 2035 (risk-neutral) and annualised CAPEX derived from the reference with discount factor of 7% for different technologies in €/kW/a, considering different EtP ratios. If the maximum allowed annualised CAPEX exceeds the option's annualised CAPEX, the corresponding RTE/EtP combination is considered a profitable investment under the given assumptions.

	RTE	EtP		
		4 h	8 h	24 h
Lithium-ion battery	92%			
Maximum allowed annualised CAPEX		101.04	143.04	182.97
Annualised CAPEX[a]		138.30	265.80	775.79
Vanadium redox flow battery	80%			
Maximum allowed annualised CAPEX		88.34	119.48	152.09
Annualised CAPEX[a]		195.01	353.13	985.60
Compressed air energy storage	70%			
Maximum allowed annualised CAPEX		76.48	98.64	125.30
Annualised CAPEX[a]		181.85	246.32	504.23
Carnot battery (low RTE)	30%			
Maximum allowed annualised CAPEX		31.78	37.96	45.52
Annualised CAPEX[b]		165.37	292.59	801.43
Carnot battery (high RTE)	73%			
Maximum allowed annualised CAPEX		80.01	104.88	133.44
Annualised CAPEX[b]		155.61	245.56	605.36

All CAPEX values in nominal €.
a [53].
b [54].

already significantly reduced, such that further investment is not economically justified. A comparison of Table 1 with Fig. 5 demonstrates that the points at which the annuity would reach parity are already located beyond the economically attractive region for additional capacity investments. Consequently, mid-term storage investments are not profitable under these scenario assumptions and market conditions if relying solely on arbitrage opportunities in the day-ahead market. This suggests that for storage technologies to become viable, additional revenue streams or market mechanisms (e.g., capacity payments or ancillary services) will be required, or a behind-the-meter application may be more favourable. Similar conclusions have been made by Taponen et al. [55] and Drury et al. [56].

From a risk perspective, technologies with a higher RTE exhibit reduced sensitivity to investors' risk preferences, resulting in more stable investment incentives under uncertainty, as illustrated in Fig. 9(a). In contrast, an increase in the EtP ratio itself only marginally affects the robustness of investment attractiveness under risk considerations for most countries (cf. Fig. 9(b)). Beyond an EtP of 72 h, further increases in the EtP ratio do not significantly alter the risk structure. This can be explained by the following reasoning. A high RTE enables the storage system to profitably exploit even smaller price spreads and, thus, is less dependent on large spreads. Conversely, a higher EtP ratio primarily increases the number, but not the magnitude, of spreads that can be utilised. These additional spreads must be large enough to ensure profitability given the corresponding RTE. Moreover, as a higher EtP ratio allows for the exploitation of a larger number of price spreads, the variation among these additional spreads decreases (cf. Fig. 4), resulting in less variation of the contribution margin between scenarios. Thus, RTE acts as a double-positive driver: it enhances absolute profitability while simultaneously minimising the exposure to market uncertainties from mean reverting processes. RTE can therefore not only be interpreted as an economic advantage but also as a risk-mitigating factor in energy storage investments. From a financial perspective, this allows for reducing the risk premium or discount rate adjustment that investors apply to uncertain revenue streams. This highlights RTE as a central parameter in evaluating the profitability and risk profile of storage investments. Additionally, the availability of long-term contracts or other hedging instruments could further mitigate revenue uncertainty and, in combination with favourable techno-economic parameters, improve investment attractiveness under market risk.

Taken together, these findings show, in accordance with the study's contributions, which mid-term storage configurations constitute profitable investment options and how their economic viability is affected by market uncertainties.

4.3. Limitations and outlook

The following limitations should be considered when evaluating the findings. This study relies on scenario data from the TYNDP 2024 Global Ambition Scenario [44] as well as weather years from the ERAA 2024 framework [43]. Therefore, the results represent estimates of potential future developments, based on current trends and technologies, but are naturally subject to uncertainty. Future technological innovations or alternative development pathways could lead to different outcomes.

Additionally, as is often done in the literature, fuel prices are modelled and assumed to exhibit mean reverting behaviour. Since there are arguments both for and against this behaviour,[11] it remains uncertain whether past patterns will persist in the future.

Furthermore, the PowerACE simulation model used in this study focuses exclusively on the day-ahead spot market for electricity. Although this market plays a central role in price formation and trading decisions, other markets, such as intraday trading, capacity markets, and balancing services, may offer additional economically relevant opportunities for storage systems. The multiplicity of markets and revenue streams and the consideration thereof in market models is an important area of future research.[12] As the consideration of these markets is beyond the scope of this study, the results may be regarded as a conservative estimate. At the same time, the long-term expansion of flexible capacity may lead to increasing competition in system service markets, potentially reducing price levels and limiting the contribution of additional revenue streams. This effect has been observed, for example, in the German market for automatic Frequency Restoration Reserve (see Nitsch et al. [25]). In such a setting, the profitability of storage systems may be driven primarily by wholesale market spreads, as these markets typically exhibit the largest traded volumes and provide the fundamental price signals in the electricity

11 For a discussion, see Pindyck (1999) [57].

12 For a discussion, see Lynch et al. (2025) [58].

system. In addition, capacity price bids in reserve markets are generally derived from the opportunity costs of not participating in the day-ahead market. Another aspect of future electricity markets that is not considered here, is the impact of sector coupling on price formation through the opportunity costs of a cross-sectoral demand, which can become price-setting [59].

Concerning the linear energy storage optimisation model, it is important to acknowledge that it operates under the assumption of perfect foresight over an entire year. As it runs outside of the PowerACE simulation and uses only the resulting price paths, this approach does not take into account the potential feedback effects on market outcomes. The results should therefore be interpreted as indicative of potential first-mover advantages or market entry opportunities under static market conditions. The lack of endogenous investments in the energy system may constrain the benefits of very high EtP configurations, as pre-existing firm capacity cannot be displaced or replaced. As this study focuses on the perspective of an individual investor rather than the entire system, the economic potential of high EtP configurations may therefore be underestimated compared to a system-level perspective. Moreover, by treating generation investments exogenously, this study cannot capture how appropriate techno-economic configurations could reduce revenue uncertainty and provide a competitive advantage over existing firm capacity, which, as shown in the literature, can otherwise facilitate investment in energy storage.

With regard to the techno-economic parameters of storage systems, it is important to note that neglecting fixed and variable costs, as well as technical characteristics such as ramp rates, degradation, or self-discharge losses, can have an impact on the robustness and accuracy of the results. In particular, storage degradation is not modelled dynamically in terms of state-of-health evolution, capacity fade, or efficiency losses over time. While this simplification is adopted in techno-economic analyses to maintain tractability, it does not capture the temporal progression of degradation or its interaction with operational strategies. In practice, storage systems may experience non-linear ageing effects, leading to a reduction in usable capacity and operational flexibility, which can affect market revenues. Therefore, the results should be interpreted as representing idealised system behaviour.[13] A more detailed degradation modelling framework tailored to specific technologies could further refine the assessment of long-term economic performance.

In addition, this study primarily focuses on uncertainties arising from mean reverting processes for fuel prices and renewable generation time series. It should be emphasised that additional sources of uncertainty, for example, those related to future expansion pathways of generation or storage infrastructure, could also have a significant impact on investment outcomes. Incorporating these factors might alter both the timing and scale of optimal investment decisions, highlighting the inherent complexity and unpredictability of long-term energy system planning.

Future research could improve the assessment of storage investment opportunities by modelling endogenous investments that directly compete with other technologies, rather than assuming static market conditions. Additionally, incorporating a broader range of uncertainties, such as path-dependency from uncertain capacity expansion, would provide a more comprehensive view of potential investment risks and timing. Finally, examining behind-the-meter applications and other alternative use cases, as well as exogenous investment incentives such as capacity remuneration mechanisms, could reveal additional pathways for achieving profitable mid-term storage investments.

[13] The high temporal resolution of the results and the use of annualised metrics (€/MW/a) allow technology developers to estimate expected revenues under reduced effective capacity levels. This enables an approximate consideration of state-of-health-related capacity losses in investment decisions, although such effects are not explicitly modelled.

5. Conclusions

Focusing on mid-term electricity storage in future energy systems, the impact of storage capacity and round-trip efficiency on investment profitability under uncertainties in fuel prices and weather conditions is assessed. By integrating mean reverting stochastic processes for fuel prices and renewable generation profiles within the PowerACE market model, the impact of these inherent uncertainties on the economic performance of storage technologies is evaluated, with a focus on wholesale market revenues. Using an inverse perspective, a wide range of combinations of technical design parameters are explored, identifying the maximum capital expenditure that allows mid-term storage configurations to remain profitable under future system conditions.

From this assessment, the following design limits and investment risk insights regarding the profitability of mid-term storage technologies are identified:

- The economic viability of technologies designed to bridge mid-term storage gaps depends primarily on their cost structure, specifically, the capital expenditure per additional unit of capacity. Technologies with lower round-trip efficiency can remain competitive if they achieve sufficiently high energy-to-power ratios while maintaining low specific capital expenditure, highlighting the critical interplay between efficiency, storage duration, and investment costs in the design of mid-term storage solutions.
- Under the examined market conditions, mid-term storage investments are not economically viable when relying solely on wholesale day-ahead arbitrage, as the marginal contribution of additional capacity is outweighed by the associated costs. To achieve financial feasibility for these technologies, alternative revenue streams are required, or additional use cases could be explored. Potential options include participation in ancillary service markets, the utilisation of political instruments such as capacity remuneration mechanisms, or other applications, for example, behind-the-meter deployment.
- Mean reverting uncertainties in fuel prices and renewable generation profiles significantly influence the profitability of storage technologies, making the identification of robust configurations essential. Efficiency plays a dual role by both increasing absolute profitability and reducing market risks. Higher round-trip efficiency decreases sensitivity to investor risk aversion, thereby stabilising the economic attractiveness of storage under uncertainty. In contrast, the energy-to-power ratio has a comparatively smaller impact on risk profiles. Beyond approximately 72 h of storage duration, further increases provide strongly limited additional benefits in terms of risk mitigation.

Overall, the results enable the identification of storage configurations that remain economically viable and robust across a range of realistic system conditions, providing actionable guidance for technology design and investors when designing storage systems and fill the mid-term storage segment in future electricity markets.

CRediT authorship contribution statement

Jonathan Stelzer: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Katharina Esser:** Writing – review & editing. **Thorsten Weiskopf:** Writing – review & editing, Software. **Armin Ardone:** Conceptualization. **Valentin Bertsch:** Writing – review & editing, Supervision, Project administration, Funding acquisition, Conceptualization. **Wolf Fichtner:** Supervision, Project administration, Conceptualization.

Research data

The data for electricity price paths and resulting contribution margins is provided and can be accessed via Zenodo: 10.5281/zenodo.17791669.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used DeeplL and ChatGPT in order to avoid grammatical and spelling errors. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Extended literature review

This section critically reviews the literature on energy storage assessment, focusing on cost-based and market-revenue-oriented methods. It highlights the limitations of conventional metrics, the partial advances of techno-economic approaches, and the remaining gap in linking technical design parameters with investment risk and economic viability under uncertainty, which is addressed in this study.

To assess and compare energy storage technologies, the literature often relies on techno-economic metrics such as the LCOS, which has been widely applied to evaluate the cost performance of different storage options under assumed technical and economic parameters. Various studies have applied LCOS calculations to a broad range of technologies. The relative cost competitiveness of these technologies is investigated, including lithium-ion batteries, pumped hydro storage, and compressed air storage [18], with redox flow batteries and hydrogen storage additionally considered [10], as well as emerging systems with gravity- or heat-based storage [60] such as Carnot batteries [19]. The reviewed studies identify battery storage as most suitable for short-duration applications and hydrogen or power-to-gas systems for seasonal storage, while assessments of compressed air energy storage and pumped hydro differ, with some studies classifying them as short- and others as mid - or long-duration options.

Further studies provide more detailed technical analyses primarily for compressed air [61] and thermal energy storage systems [62], where the respective models are optimised with respect to the LCOS. As most studies assume fixed storage durations between 6 hours - 10 h, Tassenoy et al. [63] show that Carnot batteries maximise the net present value at a 14.5 h charge and 21.8 h discharge, while McTigue et al. [64] find financial potential of Carnot batteries to compete with Li-ion batteries at charge durations above 6 h. The sensitivity analyses presented across these studies reveal that the LCOS is highly sensitive to the discharged energy volume and the electricity purchase price. Therefore, as a purely cost-based indicator, the LCOS offers only limited explanatory power for informing technology development and investment strategies. It does not adequately reflect the revenue potential that storage technologies can realise in electricity markets [9]. Consequently, additional research increasingly emphasises techno-economic modelling approaches that combine technical performance parameters with market-based revenue assessments.

These approaches enable a more comprehensive assessment of storage profitability by considering key financial indicators, including contribution margins, the net present value or the internal rate of return. Taponen et al. [55] evaluate mid-term energy storage options based on day-ahead and intraday market prices for Finland in 2023. They find that, while day-ahead trading alone is not economically viable, intraday operations can improve profitability. With a focus on the investor perspective, Spodniak et al. [20] investigate key factors influencing the economic viability of large-scale, centralised electricity storage in the day-ahead markets in Germany, the UK and Scandinavia during the period 2006–2016 for different EtP ratios. They find that for the markets and time-frame considered, the marginal increase in contribution margins decreases quickly as the EtP ratio is increased. By analysing lithium-ion battery performance in day-ahead markets in 22 countries (2016–2022), Komorowska et al. [21] find that batteries yield a negative net present value under their capital costs assumptions for 2022. Poli et al. [22] came to the same conclusion for redox-flow batteries, evaluating them in the Italian market. Cetegen et al. [23] find that a liquid air energy storage in the Texas electricity market with a 16 h charge and 8 h discharge can cover both CAPEX and operational expenditure, whereas Vecchi et al. [24] show in a UK case how simultaneous participation in reserve markets can further increase revenues. Similarly, Nitsch et al. [25] simulate the German day-ahead and automatic frequency restoration reserve markets to evaluate revenue potentials of battery storage using an agent-based electricity market model. For a 2030 market with high shares of renewable energies, they find that compared to 2019, the economic potential will increase and so will the importance of the day-ahead market.

Nevertheless, even within more market-based modelling frameworks, most studies still rely on predefined cost assumptions and focus on specific storage technologies. While such analyses can indicate whether a given technology may be economically viable under certain conditions, they do not provide insights into how storage systems should be designed or which techno-economic parameter combinations (i.e., investment cost, storage capacity, or round-trip efficiency) would enable profitability. Consequently, there is a need for approaches that explicitly link technical design parameters to economic feasibility. Esser et al. [11] develop a multi-objective inverse modelling approach that links technical design parameters directly to generation expansion planning. They demonstrate their approach for Carnot batteries using a model setup that includes five European countries in the target year 2050 under full decarbonisation conditions, and find that the maximum allowable CAPEX at which these systems remain endogenously deployed is low, at around 140 €/kW (12 €/kW/a). However, higher EtP ratios effectively improves allowable CAPEX. For the same target year under a full decarbonisation scenario, Nitsch et al. [26] combine generation expansion with market modelling to show that Carnot batteries become economical at annualised CAPEX levels of 25–27 €/kW/a for EtP ratios of 7–8 h and 3.7–35.8 GW of installed capacity. Sorknæs et al. [27] investigate the system cost reduction potential of Carnot batteries in a 100% renewable Danish energy system for the target year 2045. They identify an economic threshold of 60–66 €/MWh for discharging costs, corresponding to annualised CAPEX of roughly 165 €/kW/a. By integrating Carnot batteries exogenously into the German electricity market for the years 2030–2040, Stelzer et al. [28] conclude that higher EtP ratios of Carnot batteries lead to lower profitability, as the additional revenue does not fully compensate for the increased costs associated with the larger EtP ratio. Together, these studies advance storage analysis toward integrated generation expansion and competitiveness perspectives, revealing thresholds of emerging storage technologies to enter and sustain market relevance. However, these techno-economic assessments do not capture the full extent of inherent risks and uncertainties in future energy market conditions, including fluctuating electricity prices and renewable generation variability.

Studies that combine investment risk and uncertainty with storage valuation tend to move away from identifying maximum cost thresholds or applying inverse modelling approaches. Instead, they focus again on predefined technology configurations and parameter sets, thereby limiting insights into how design choices influence economic feasibility under uncertainty. Geske et al. [29] use a Markov decision model to optimise storage capacity under uncertain residual load (from demand and wind/solar variability), finding that these uncertainties increase effective storage costs by 27% from 4.1 €/kWh to the perfect-foresight value of 5.6 €/kWh. In addition, Hammann et al. [30] apply a real options approach to evaluate the option value of adiabatic compressed air energy storage, where uncertainties such as varying natural gas prices lead to a high option value. Bakke et al. [31] have analysed the profitability of lithium-ion battery investments under variable spot and balancing prices, showing that high uncertainty in future battery costs leads investors to postpone investment decisions until additional information becomes available. Nevertheless, stochastic equilibrium models have been applied to explicitly modelling market interactions, risk hedging opportunities, and the impact of incomplete long-term contracts on investment decisions. For instance, de Maere d'Aertrycke et al. [13] show that incomplete long-term contracting can significantly reduce investment incentives in the restructured power sector, and that the effectiveness of long-term instruments such as contracts for differences or forward capacity markets depends critically on market liquidity and proper calibration. Their stochastic simulations indicate that risk exposure, risk aversion, and the extent of risk trading drastically influence investment outcomes, highlighting the importance of carefully designed hedging mechanisms to support profitable and timely deployment of clean energy technologies. In the context of energy storage, Makrides et al. [35] apply a two-stage stochastic equilibrium model to examine how missing risk markets affect investment in storage under uncertainty. They show that limited hedging opportunities increase the cost of capital and disproportionately constrain the energy rather than the power capacity of storage, highlighting the importance of de-risking mechanisms and supplementary revenue streams to support investment in high-capital, reliability-enhancing technologies. While such approaches provide valuable insights into investment risk, they fall short of linking the underlying techno-economic parameters to the resulting investment feasibility, particularly in terms of how storage systems should be designed to remain attractive under incomplete hedging opportunities or missing risk markets.

Appendix B. Input assumptions and additional results

B.1. Capacities of energy system trajectory

See Table B.2.

B.2. Weather scenario weights

See Table B.3.

B.3. Empirical covariance matrix of historical fuel prices and parameters of the multivariate OU process

See Tables B.4 and B.5.

B.4. Representative fuel price paths

See Fig. B.10.

Table B.2
Capacities and total demand in the fixed energy system path for each country.

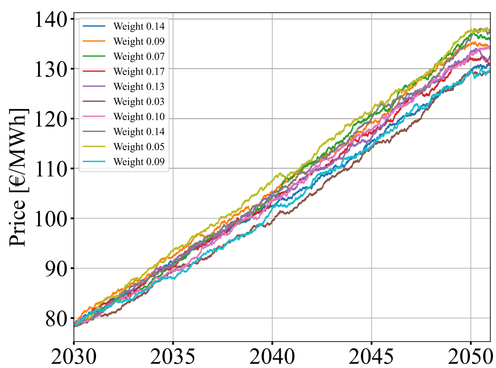
	2035	2040	2045	Unit
Germany				
Total electricity demand	892.84	1021.25	1145.83	[TWh]
Natural gas turbine	79.41	67.16	33.58	[GW]
Hydrogen turbine	17.13	25.44	45.01	[GW]
Wind	192.27	225.75	243.92	[GW]
Solar	299.47	383.95	420.17	[GW]
Other renewable/thermal	13.24	9.76	8.2	[GW]
Reservoir	0.81	0.81	0.81	[GW]
Lithium-ion batteries	50.17	78.53	99.80	[GW]
Pumped hydro storage	9.37	10.73	10.73	[GW]
Electric vehicles	26.23	48.74	48.74	[GW]
Demand side response	20.10	20.94	21.67	[GW]
Electrolyser	22.71	36.79	60.24	[GW]
France				
Total electricity demand	559.57	636.56	701.80	[TWh]
Natural gas turbine	6.5	6.02	491	[GW]
Hydrogen turbine	0.78	1.56	428	[GW]
Nuclear	64.50	66.00	58.06	[GW]
Wind	67.98	87.37	105.87	[GW]
Solar	93.7	122.57	158.08	[GW]
Other renewable/thermal	16.01	16.01	16.01	[GW]
Reservoir	9.84	9.84	9.84	[GW]
Lithium-ion batteries	3.35	6.66	10.23	[GW]
Pumped hydro storage	4.24	4.84	5.46	[GW]
Electric vehicles	22.43	34.91	41.09	[GW]
Demand side response	6.50	6.50	6.50	[GW]
Electrolyser	4.18	10.42	19.80	[GW]
Switzerland				
Total electricity demand	65.55	72.78	73.09	[TWh]
Wind	0.73	1.15	1.69	[GW]
Solar	9.77	10.1	11.71	[GW]
Other renewable/thermal	4.71	4.93	5.21	[GW]
Reservoir	8.73	8.93	9.05	[GW]
Lithium-ion batteries	0.67	1.11	1.56	[GW]
Pumped hydro storage	5.19	6.02	6.14	[GW]
Electrolyser	0.26	0.26	0.26	[GW]
Denmark				
Total electricity demand	104.48	131.64	150.75	[TWh]
Natural gas turbine	1.52	1.11	1.11	[GW]
Hard coal	1.24	1.17	1.17	[GW]
Wind	30.8	37.8	44.55	[GW]
Solar	21.71	22.32	23.38	[GW]
Other renewable/thermal	0.75	0.75	0.75	[GW]
Lithium-ion batteries	0.53	0.53	0.55	[GW]
Electric vehicles	0.55	0.91	1.93	[GW]
Electrolyser	19.60	29.12	35.07	[GW]
Spain				
Total electricity demand	403.38	474.05	501.07	[TWh]
Natural gas turbine	20.51	20.51	17.71	[GW]
Wind	79.66	85.83	91.99	[GW]
Solar	103.09	134.73	144.74	[GW]
Other renewable/thermal	5.15	5.15	5.15	[GW]
Reservoir	11.41	11.41	11.41	[GW]
Lithium-ion batteries	4.60	7.4	8.3	[GW]
Pumped hydro storage	11.13	11.73	12.73	[GW]
Electric vehicles	15.29	24.06	28.35	[GW]
Demand side response	2.70	3.50	3.75	[GW]
Electrolyser	29.00	32.75	39.15	[GW]

B.5. Contribution margins for storage parameter combinations for a risk-neutral investor

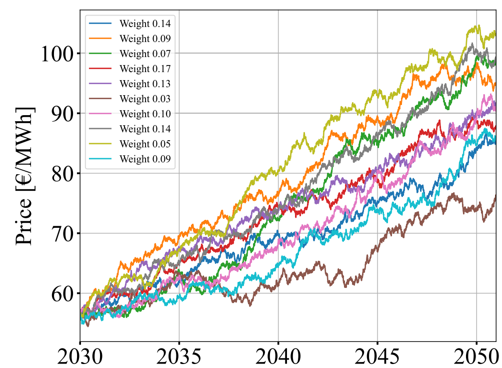
See Fig. B.11.

B.6. Contribution margins for storage parameter combinations for a risk-averse investor

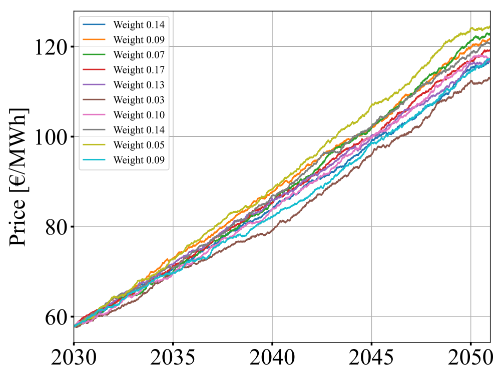
See Fig. B.12.



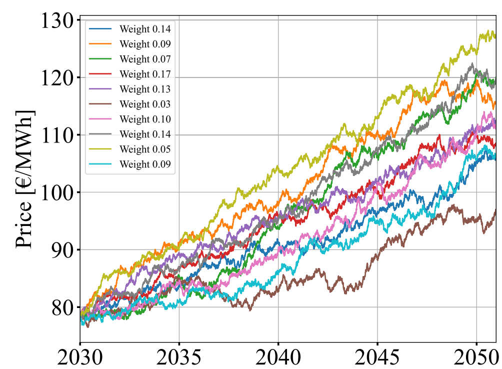
(a) Cluster representatives for crude oil, weighted by path probability.



(b) Cluster representatives for natural gas, weighted by path probability.



(c) Cluster representatives for hard coal, weighted by path probability.



(d) Cluster representatives for Hydrogen, weighted by path probability.

Fig. B.10. Cluster representative fuel price paths for each fuel type over the full time horizon, with legend indicating the weight of each path.

B.7. Sensitivity to system-pathway

To account for an alternative system pathway, the methodology is additionally applied using a fixed energy system pathway from the TYNDP 2024 Distributed Energy Scenario. Fig. B.13 presents the results for Germany in 2035. The overall behaviour is consistent with that observed under the Global Ambitions scenario. Although the absolute magnitude of the maximum annualised CAPEX differs between the scenarios, the qualitative trends remain unchanged.

B.8. Sensitivity to charge power and discharge power

As shown in Figs. B.14 and B.15, a reduction in discharge power at constant charge power results in a smaller loss of contribution margin than the reverse. This is because, in the assumed scenario, a high capacity of electrolysers and electric vehicles operate for many hours under dominant renewable generation. Because this generation has historically caused very low prices, the operation of sector-coupling technologies in this scenario raises the overall price level. Conversely, high storage and flexibility smooth price peaks, resulting in only a few low-price hours and longer consecutive high-price hours.

B.9. Sensitivity to variable operating and maintenance costs and self-discharge

The given scenario is also applied to the following storage configurations, considering a variable operating and maintenance cost of 5 €/MWh, as summarised in Table B.6. It can be seen that storage systems with higher RTE are less affected by these costs.

The same analysis is applied to the impact of self-discharge of 1% per day on different storage configurations, shown in Table B.7. It can be seen that storage systems with higher RTE are less affected, while higher EtP ratios increase the effect.

Appendix C. Additional methods

C.1. Average daily spreads

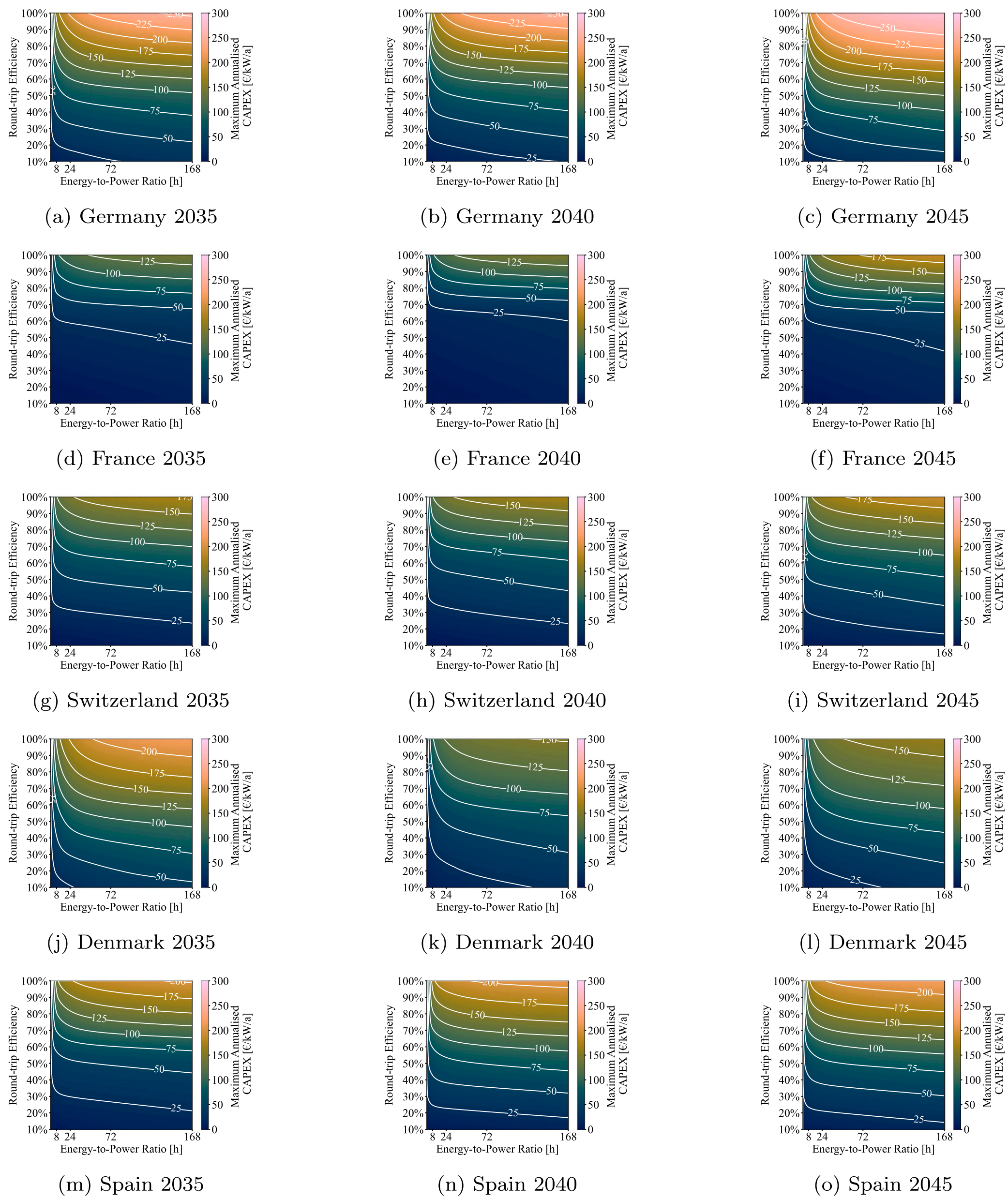
The average daily spreads, shown in Fig. 4, are calculated as follows: For each day d, let $P_{d,1}, P_{d,2}, \dots, P_{d,24}$ denote the set of hourly prices. The nth largest and nth smallest prices are defined as $P^{\downarrow}_{d,(n)}$ and $P^{\uparrow}_{d,(n)}$, respectively. The daily n-spread is computed as

$$S^{(n)}_d = P^{\downarrow}_{d,(n)} - P^{\uparrow}_{d,(n)}.$$

The mean daily n-spread over all days D is

$$\overline{S}^{(n)} = \frac{1}{|D|} \sum_{d \in D} S^{(n)}_d.$$

$S^{(n)}_d$ represents the difference between the nth largest and nth smallest hourly price within a single day, and $\overline{S}^{(n)}$ summarises this measure across the entire dataset.



(a) Germany 2035 (b) Germany 2040 (c) Germany 2045

(d) France 2035 (e) France 2040 (f) France 2045

(g) Switzerland 2035 (h) Switzerland 2040 (i) Switzerland 2045

(j) Denmark 2035 (k) Denmark 2040 (l) Denmark 2045

(m) Spain 2035 (n) Spain 2040 (o) Spain 2045

Fig. B.11. Maximum annualised CAPEX for all analysed countries (rows) and years (columns) with $\lambda = 0$.

C.2. Mathematical representation of weather scenario weights

A total of I weather scenarios $i \in \mathcal{I} = \{1, \dots, I\}$ are considered, each with hourly values for renewable generation capacity factors and electricity demand as component $c \in \mathcal{C}$. The scenario probability w_i^w is computed through a weighted aggregation over areas $a = 1, \dots, A$, components $c = 1, \dots, C$, and months $m = 1, \dots, 12$. For each component c in area a and month m, the monthly mean over hours h is calculated as:

$$\bar{x}_{i,a,c,m} = \frac{1}{n_m^h} \sum_{h \in \text{ month } m} x_{i,a,c,h} \tag{C.1}$$

where $x_{i,a,c,h}$ denotes the hourly value of scenario i, component c, and area a, and n_m^h is the number of hours in month m. The monthly mean across all scenarios is

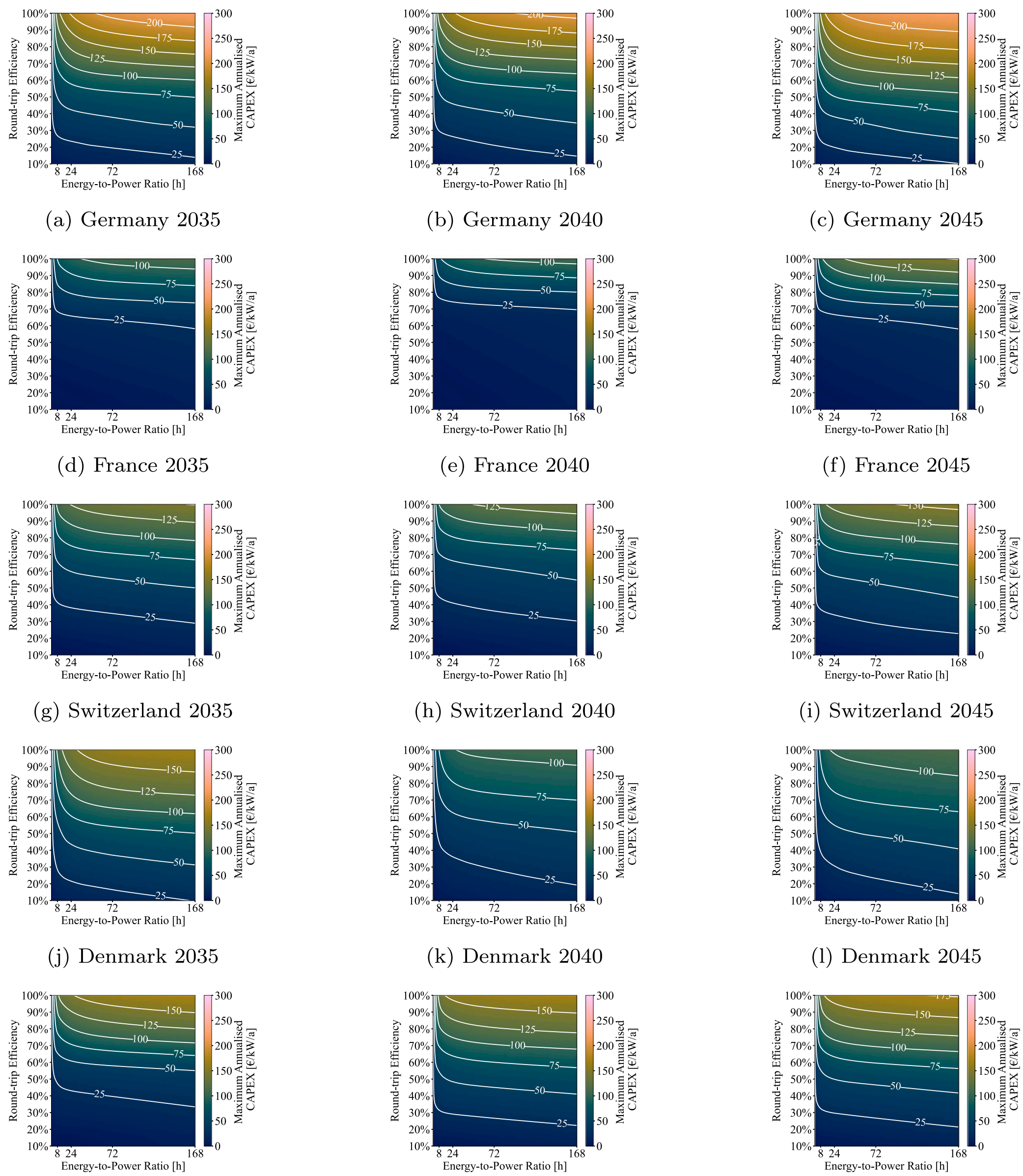
$$\mu_{a,c,m} = \frac{1}{|\mathcal{I}|} \sum_{i \in \mathcal{I}} \bar{x}_{i,a,c,m} \tag{C.2}$$

The deviation of a scenario from the mean is

$$\Delta_{i,a,c,m} = \bar{x}_{i,a,c,m} - \mu_{a,c,m} \tag{C.3}$$

The standard deviation across scenarios is

$$\sigma_{a,c,m} = \sqrt{\frac{1}{|\mathcal{I}|} \sum_{i \in \mathcal{I}} (\bar{x}_{i,a,c,m} - \mu_{a,c,m})^2} \tag{C.4}$$



(a) Germany 2035 (b) Germany 2040 (c) Germany 2045

(d) France 2035 (e) France 2040 (f) France 2045

(g) Switzerland 2035 (h) Switzerland 2040 (i) Switzerland 2045

(j) Denmark 2035 (k) Denmark 2040 (l) Denmark 2045

(m) Spain 2035 (n) Spain 2040 (o) Spain 2045

Fig. B.12. Maximum annualised CAPEX for all analysed countries (rows) and years (columns) with $\lambda = 1$.

The deviation is assigned to bins as follows:

$$\text{Bin}_{i,a,c,m} = \begin{cases} \text{Bin 1}, & \Delta_{i,a,c,m} < -2\sigma_{a,c,m} \\ \text{Bin 2}, & -2\sigma_{a,c,m} \leq \Delta_{i,a,c,m} < -\sigma_{a,c,m} \\ \text{Bin 3}, & -\sigma_{a,c,m} \leq \Delta_{i,a,c,m} < 0 \\ \text{Bin 4}, & 0 \leq \Delta_{i,a,c,m} < \sigma_{a,c,m} \\ \text{Bin 5}, & \sigma_{a,c,m} \leq \Delta_{i,a,c,m} < 2\sigma_{a,c,m} \\ \text{Bin 6}, & \Delta_{i,a,c,m} \geq 2\sigma_{a,c,m} \end{cases} \tag{C.5}$$

The probability per bin is

$$w^{\text{bin}}_{i,a,c,m} = \frac{\text{Number of scenarios in the same bin}}{|\mathcal{I}|} \tag{C.6}$$

The component weight is

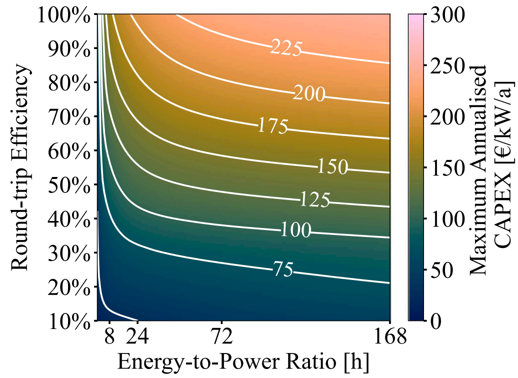
$$w^{\text{comp}}_{a,c} = \frac{\text{Capacity or demand of component } c \text{ in area } a}{\sum_{a'=1}^{A} \text{Capacity or demand of component } c \text{ in all areas}} \tag{C.7}$$

The total scenario probability is computed by summing over all areas, components, and months:

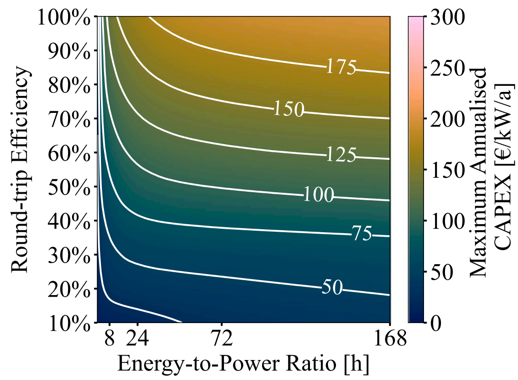
$$w^{w}_{i} = \sum_{a=1}^{A} \sum_{c=1}^{C} \sum_{m=1}^{12} w^{\text{comp}}_{a,c} \cdot w^{\text{bin}}_{i,a,c,m} \tag{C.8}$$

with

$$\sum_{i \in \mathcal{I}} w^{w}_{i} = 1$$

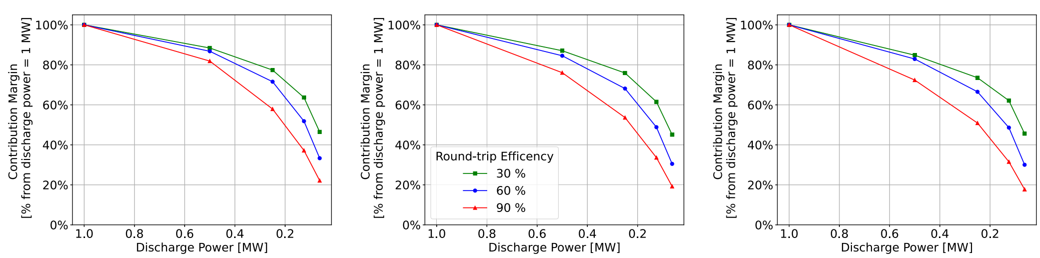


(a) Maximum annualised CAPEX π^* (cf. Equation 13) in Germany (2035) for a risk-neutral investor ($\lambda = 0$).



(b) Maximum annualised CAPEX π^* (cf. Equation 13) in Germany (2035) for a risk-averse investor ($\lambda = 1$).

Fig. B.13. Maximum annualised CAPEX π^* (cf. Eq. (13)) in Germany (2035) for a risk-averse investor ($\lambda = 1$).

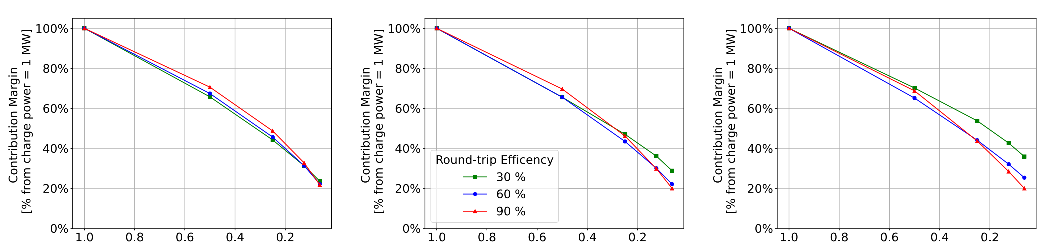


(a) 8 h Energy-to-Power (EtP) ratio

(b) 24 h Energy-to-Power (EtP) ratio

(c) 72 h Energy-to-Power (EtP) ratio

Fig. B.14. Relative contribution margin [% of the reference at 1 MW discharge power] as a function of reduced discharge power for different RTE and EtP ratios, while the charge power remains fixed at 1 MW. For example, a value of 0.5 on the x-axis represents the configuration at 1 MW charge and 0.5 MW discharge, and the y-value gives the contribution margin relative to the 1 MW/1 MW reference case.



(a) 8 h Energy-to-Power (EtP) ratio

(b) 24 h Energy-to-Power (EtP) ratio

(c) 72 h Energy-to-Power (EtP) ratio

Fig. B.15. Relative contribution margin [% of the reference at 1 MW charge power] as a function of reduced charge power for different RTE and EtP ratios, while the discharge power remains fixed at 1 MW. For example, a value of 0.5 on the x-axis represents the configuration at 1 MW discharge and 0.5 MW charge, and the y-value gives the contribution margin relative to the 1 MW/1 MW reference case.

Table B.3
Weather scenario weights for ERAA 2024 weather scenario capacity factor profiles.

Scenario	2035	2040	2045
WS1	0.025655	0.028575	0.028580
WS2	0.027332	0.028470	0.028476
WS3	0.028940	0.030704	0.030719
WS4	0.027652	0.027183	0.027151
WS5	0.031591	0.028482	0.028501
WS6	0.030094	0.027443	0.027461
WS7	0.033703	0.029007	0.028981
WS8	0.028069	0.028446	0.028392
WS9	0.027828	0.029552	0.029479
WS10	0.031980	0.030164	0.030222
WS11	0.028304	0.026438	0.026453
WS12	0.032032	0.029264	0.029239
WS13	0.030445	0.028291	0.028295
WS14	0.028848	0.028318	0.028255
WS15	0.018540	0.024816	0.024843
WS16	0.020470	0.026941	0.026933
WS17	0.028312	0.025594	0.025608
WS18	0.027452	0.027076	0.027079
WS19	0.017281	0.023767	0.023791
WS20	0.030023	0.029914	0.029914
WS21	0.032243	0.028905	0.028915
WS22	0.023606	0.025715	0.025765
WS23	0.029310	0.028105	0.028108
WS24	0.023566	0.024748	0.024810
WS25	0.028857	0.027420	0.027428
WS26	0.027353	0.027433	0.027451
WS27	0.026537	0.026931	0.026914
WS28	0.029302	0.029757	0.029767
WS29	0.030190	0.027404	0.027374
WS30	0.029525	0.030467	0.030469
WS31	0.018973	0.021817	0.021843
WS32	0.028389	0.026216	0.026162
WS33	0.029915	0.027962	0.028012
WS34	0.031944	0.031927	0.031882
WS35	0.026139	0.027577	0.027563
WS36	0.029597	0.029172	0.029167

Table B.4
Parameters of the multivariate OU process.

Parameter	Hard coal	Natural gas	Crude oil	Hydrogen
X_0 [a]	78.55	56.48	57.76	78.50
μ [a]	134.54	95.65	119.36	112.20
θ	0.04	0.03	0.03	0.03
σ	0.60	1.29	0.50	1.29

[a] In nominal €.

Table B.5
Covariance matrix for multivariate OU process.

	Crude oil	Natural gas	Hard coal	Hydrogen
Crude oil	0.23	0.49	0.23	0.49
Natural gas	0.49	1.67	0.49	1.67
Hard coal	0.23	0.49	0.25	0.49
Hydrogen	0.49	1.67	0.49	1.67

Table B.6
Impact of variable operating and maintenance costs on different storage configurations for a risk neutral investor in Germany 2035. Values indicate contribution margin reduction.

RTE	EtP		
	8 h	24 h	72 h
0.3	−17.78%	−15.60%	−13.06%
0.6	−11.98%	−12.05%	−12.39%
0.9	−9.53%	−9.13%	−8.82%

Table B.7
Impact of self-discharge on different storage configurations for a risk neutral investor in Germany 2035. Values indicate contribution margin reduction.

RTE	EtP		
	8 h	24 h	72 h
0.3	−0.42%	−1.22%	−2.79%
0.6	−0.19%	−0.51%	−1.17%
0.9	−0.07%	−0.16%	−0.37%

Data availability

The data for electricity price paths and the resulting contribution margins are available at Zenodo: https://doi.org/10.5281/zenodo.17791669. All other data used in this study cannot be shared publicly due to restrictions but are available from the sources cited in the paper.

References

[1] Intergovernmental Panel on Climate Change (IPCC). Global warming of 1.5 °C: An IPCC special report on the impacts of global warming of 1.5 °C above pre-industrial levels and related global greenhouse gas emission pathways. 2018, https://www.ipcc.ch/sr15/.

[2] International Energy Agency (IEA). Renewables 2025. 2025, https://www.iea.org/reports/renewables-2025.

[3] Gorenstein Dedecca J, Ansarin M, Bene C, van Delzen T, van Nuffel L, Jagtenberg H. Increasing flexibility in the EU energy system: Technologies and policies to enable the integration of renewable electricity sources. 2025, https://www.europarl.europa.eu/thinktank/en/document/ECTI_STU(2025)769347.

[4] Guerra OJ, Zhang J, Eichman J, Denholm P, Kurtz J, Hodge B-M. The value of seasonal energy storage technologies for the integration of wind and solar power. Energy Environ Sci 2020;13:1909–22. http://dx.doi.org/10.1039/D0EE00771D.

[5] Dowling JA, Rinaldi KZ, Ruggles TH, Davis SJ, Yuan M, Tong F, Lewis NS, Caldeira K. Role of long-duration energy storage in variable renewable electricity systems. Joule 2020;4(9):1907–28. http://dx.doi.org/10.1016/j.joule.2020.07.007.

[6] Helbig C, Bradshaw AM, Wietschel L, Thorenz A, Tuma A. Supply risks associated with lithium-ion battery materials. J Clean Prod 2018;172:274–86. http://dx.doi.org/10.1016/j.jclepro.2017.10.122.

[7] Fazeli R, Beck FJ, Stocks M. Recognizing the role of uncertainties in the transition to renewable hydrogen. Int J Hydrog Energy 2022;47(65):27896–910. http://dx.doi.org/10.1016/j.ijhydene.2022.06.122.

[8] Odenweller A, Ueckerdt F. The green hydrogen ambition and implementation gap. Nat Energy 2025;10:110–23. http://dx.doi.org/10.1038/s41560-024-01684-7.

[9] Bertsch V, Finke J, Esser K, Plaga L, Mersch M, Stelzer J, Atakan B, Fichtner W, Markides C, Sioshansi R. How can energy-system models inform technology development? Insights for emerging energy-storage technologies. Int J Electr Power Energy Syst 2025;173:111360. http://dx.doi.org/10.1016/j.ijepes.2025.111360.

[10] Schmidt O, Melchior S, Hawkes A, Staffell I. Projecting the future levelized cost of electricity storage technologies. Joule 2019;3(1):81–100. http://dx.doi.org/10.1016/j.joule.2018.12.008.

[11] Esser K, Finke J, Bertsch V. A multi-objective inverse (MOIn) energy system modelling method for guiding early technology development. Energy Convers Manage 2026;347:120520. http://dx.doi.org/10.1016/j.enconman.2025.120520.

[12] Fraunholz C, Miskiw KK, Kraft E, Fichtner W, Weber C. On the role of risk aversion and market design in capacity expansion planning. Energy J 2023;44(3):111–38. http://dx.doi.org/10.5547/01956574.44.2.cfra.

[13] de Maere d'Aertrycke G, Ehrenmann A, Smeers Y. Investment with incomplete markets for risk: The need for long-term contracts. Energy Policy 2017;105:571–83. http://dx.doi.org/10.1016/j.enpol.2017.01.029.

[14] Newbery D. Missing money and missing markets: Reliability, capacity auctions and interconnectors. Energy Policy 2016;94:401–10. http://dx.doi.org/10.1016/j.enpol.2015.10.028.

[15] Zhou Z, Botterud A, Levin T. Price formation in zero-carbon electricity markets – fundamentals, challenges, and research needs. Renew Sustain Energy Rev 2025;211:115250. http://dx.doi.org/10.1016/j.rser.2024.115250.

[16] Martin-Valmayor MA, Gil-Alana LA, Infante J. Energy prices in Europe. Evidence of persistence across markets. Resour Policy 2023;82:103546. http://dx.doi.org/10.1016/j.resourpol.2023.103546.

[17] Badosa J, Gobet E, Grangereau M, Kim D. Day-ahead probabilistic forecast of solar irradiance: A stochastic differential equation approach. Springer proceedings in mathematics & statistics, vol. 254, 2018, http://dx.doi.org/10.1007/978-3-319-99052-1_4.

[18] Obi M, Jensen SM, Ferris JB, Bass RB. Calculation of levelized costs of electricity for various electrical energy storage systems. Renew Sustain Energy Rev 2017;67:908–20. http://dx.doi.org/10.1016/j.rser.2016.09.043.

[19] Smallbone A, Jülch V, Wardle R, Roskilly AP. Levelised cost of storage for pumped heat energy storage in comparison with other energy storage technologies. Energy Convers Manage 2017;152:221–8. http://dx.doi.org/10.1016/j.enconman.2017.09.047.

[20] Spodniak P, Bertsch V, Devine M. The profitability of energy storage in European electricity markets. Energy J 2021;42(5):221–46.

[21] Komorowska A, Olczak P. Economic viability of li-ion batteries based on the price arbitrage in the European day-ahead markets. Energy 2024;290:130009. http://dx.doi.org/10.1016/j.energy.2023.130009.

[22] Poli N, Bonaldo C, Moretto M, Guarnieri M. Techno-economic assessment of future vanadium flow batteries based on real device/market parameters. Appl Energy 2024;362:122954. http://dx.doi.org/10.1016/j.apenergy.2024.122954.

[23] Cetegen SA, Gundersen T, Barton PI. Evaluating economic feasibility of liquid air energy storage systems in US and European markets. Energy 2024;300:131524. http://dx.doi.org/10.1016/j.energy.2024.131524.

[24] Vecchi A, Naughton J, Li Y, Mancarella P, Sciacovelli A. Multi-mode operation of a liquid air energy storage (LAES) plant providing energy arbitrage and reserve services – analysis of optimal scheduling and sizing through MILP modelling with integrated thermodynamic performance. Energy 2020;200:117500. http://dx.doi.org/10.1016/j.energy.2020.117500.

[25] Nitsch F, Deissenroth-Uhrig M, Schimeczek C, Bertsch V. Economic evaluation of battery storage systems bidding on day-ahead and automatic frequency restoration reserves markets. Appl Energy 2021;298:117267.

[26] Nitsch F, Wetzel M, Gils HC, Nienhaus K. The future role of carnot batteries in central Europe: Combining energy system and market perspective. J Energy Storage 2024;85:110959. http://dx.doi.org/10.1016/j.est.2024.110959.

[27] Sorknæs P, Thellufsen JZ, Knobloch K, Engelbrecht K, Yuan M. Economic potentials of Carnot batteries in 100% renewable energy systems. Energy 2023;282:128837. http://dx.doi.org/10.1016/j.energy.2023.128837.

[28] Stelzer J, Ardone A, Fichtner W. Modeling the impact of mid-term storage on electricity markets: Insights from carnot battery integration. In: 21st international conference on the European energy market. EEM, 2025, http://dx.doi.org/10.1109/EEM64765.2025.11050107.

[29] Geske J, Green R. Optimal storage, investment and management under uncertainty: It is costly to avoid outages!. Energy J 2020;41(2):1–28. http://dx.doi.org/10.5547/01956574.41.2.jges.

[30] Hammann E, Madlener R, Hilgers C. Economic feasibility of a compressed air energy storage system under market uncertainty: A real options approach. Energy Procedia 2017;105:3798–805. http://dx.doi.org/10.1016/j.egypro.2017.03.888.

[31] Bakke I, Fleten S-E, Hagfors LI. Investment in electric energy storage under uncertainty: a real options approach. Comput Manag Sci 2016;13:483–500. http://dx.doi.org/10.1007/s10287-016-0256-3.

[32] Dimanchev E, Gabriel SA, Reichenberg L, Korpås M. Consequences of the missing risk market problem for power system emissions. Energy Econ 2024;136:107639. http://dx.doi.org/10.1016/j.eneco.2024.107639.

[33] Friedel L, Grenz J, Hagist C. A comparison of long duration energy storage technologies based on levelized cost of storage. J Energy Storage 2026;153:120679. http://dx.doi.org/10.1016/j.est.2026.120679.

[34] Mantegna G, Ricks W, Manocha A, Patankar N, Mallapragada D, Jenkins J. Establishing best practices for modeling multi-day energy storage in deeply decarbonized energy systems. Environ Res: Energy 2024;1(4):045014. http://dx.doi.org/10.1088/2753-3751/ad96bd.

[35] Makrides AC, Suski A, Spyrou E. Quantifying the impact of missing risk markets for decarbonized power systems with long duration energy storage. 2025, http://dx.doi.org/10.48550/arXiv.2510.13514, arXiv Preprint arXiv:2510.13514.

[36] Fraunholz C. Market design for the transition to renewable electricity systems (Ph.D. thesis), Karlsruher Institut für Technologie (KIT); 2021, http://dx.doi.org/10.5445/IR/1000133282.

[37] Benth FE, Kallsen J, Meyer-Brandis T. A non-Gaussian Ornstein–Uhlenbeck process for electricity spot price modeling and derivatives pricing. Appl Math Finance 2007;14(2):153–69. http://dx.doi.org/10.1080/13504860600725031.

[38] Ogbogbo CP. Modeling crude oil spot price as an Ornstein–Uhlenbeck process. Int J Math Sci Optim: Theory Appl 2018;2018:261–75, URL https://ijmso.unilag.edu.ng/article/view/25.

[39] Tweneboah OK. Applications of ornstein–uhlenbeck type stochastic differential equations (Doctor of philosophy (ph.d.) thesis), University of Texas at El Paso; 2020, Open Access Theses & Dissertations no. 3052. URL https://scholarworks.utep.edu/open_etd/3052.

[40] Chaiyapo N, Phewchean N. An application of Ornstein–Uhlenbeck process to commodity pricing in Thailand. Adv Difference Equ 2017;2017(179). http://dx.doi.org/10.1186/s13662-017-1234-y.

[41] Ornstein LS, Uhlenbeck GE. On the theory of the Brownian motion. Phys Rev 1930;36(5):823–41. http://dx.doi.org/10.1103/PhysRev.36.823.

[42] Benth FE, Benth JS, Koekebakker S. Stochastic modeling of electricity and related markets. World Scientific; 2008, http://dx.doi.org/10.1142/6811.

[43] European Network of Transmission System Operators for Electricity (ENTSO-E). European resource adequacy assessment – 2024 edition: executive report (ACER's approved and amended version, August 2025). Technical report, ENTSO-E; 2025, ACER's approved and amended version.

[44] European Network of Transmission System Operators for Electricity (ENTSO-E). TYNDP 2024: scenario report. Tech. rep., ENTSO-E; 2025, URL https://2024.entsos-tyndp-scenarios.eu/.

[45] Fein-Ashley J. A comparison of traditional and deep learning methods for parameter estimation of the Ornstein–Uhlenbeck process. 2024, http://dx.doi.org/10.48550/arXiv.2404.11526, ArXiv Preprint.

[46] Curcio E. Techno-economic analysis of hydrogen production: Costs, policies, and scalability in the transition to net-zero. 2025, http://dx.doi.org/10.48550/arXiv.2502.12211, ArXiv Preprint.

[47] International Monetary Fund. World economic outlook: policy pivot, rising threats. October 2024 ed.. International Monetary Fund; 2024.

[48] Bublitz A, Keles D, Fichtner W. An analysis of the decline of electricity spot prices in Europe: Who is to blame? Energy Policy 2017;107:323–36. http://dx.doi.org/10.1016/j.enpol.2017.04.034.

[49] Zimmermann F, Bublitz A, Keles D, Fichtner W. Cross-border effects of capacity remuneration mechanisms: The swiss case. Energy J 2021;42(2):53–90. http://dx.doi.org/10.5547/01956574.42.2.fzim.

[50] Signer T, Baumgartner N, Ruppert M, Sandmeier T, Fichtner W. Modeling V2G spot market trading: The impact of charging tariffs on economic viability. Energy Policy 2024;189:114109. http://dx.doi.org/10.1016/j.enpol.2024.114109.

[51] Sioshansi R, Denholm P, Jenkin T, Weiss J. Estimating the value of electricity storage in PJM: Arbitrage and some welfare effects. Energy Econ 2009;31(2):269–77. http://dx.doi.org/10.1016/j.eneco.2008.10.005.

[52] Sepulveda NA, Jenkins JD, Edington A, Hoff TE, Holttinen H, Meibom P, de Sisternes FJ, Botterud A. The design space for long-duration energy storage in decarbonized power systems. Nat Energy 2021;6:506–16. http://dx.doi.org/10.1038/s41560-021-00796-8.

[53] Danish Energy Agency, Energinet. Technology data energy storage. Tech. rep., Danish Energy Agency; 2018, URL https://ens.dk/en/analyses-and-statistics/technology-data-energy-storage.

[54] Dumont O, Frate GF, Pillai A, Lecompte S, De Paepe M, Lemort V. Carnot battery technology: A state-of-the-art review. J Energy Storage 2020;32:101756. http://dx.doi.org/10.1016/j.est.2020.101756.

[55] Taponen P, Adetunji A, Koponen K, Pongracz E. Economic feasibility of medium-term energy storage for intermittent power producer. J Energy Storage 2025;120:116519. http://dx.doi.org/10.1016/j.est.2025.116519.

[56] Drury E, Denholm P, Sioshansi R. The value of compressed air energy storage in energy and reserve markets. Energy 2011;36(8):4959–73. http://dx.doi.org/10.1016/j.energy.2011.05.041.

[57] Pindyck RS. The long-run evolution of energy prices. Energy J 1999;20(2):1–27. http://dx.doi.org/10.5547/ISSN0195-6574-EJ-Vol20-No2-1.

[58] Lynch MÁ, Bertsch V. Lessons from wholesale market success for system service procurement design in high renewable electricity markets. Nat Energy 2025;10(2):166–71.

[59] Johanndeiter S, Helistö N, Kiviluoma J, Bertsch V. Price formation and intersectoral distributional effects in a fully decarbonised european electricity market. Adv Appl Energy 2025;100245.

[60] Mugyema M, Botha CD, Kamper MJ, Wang R-J, Sebitosi AB. Levelised cost of storage comparison of energy storage systems for use in primary response application. J Energy Storage 2023;59:106573. http://dx.doi.org/10.1016/j.est.2022.106573.

[61] Zhang Y, Liu J, Yin S, Su C, Liu Z. Design and performance analysis of a novel compressed air-liquid CO_2 energy storage. Energy Convers Manage 2024;301:118068. http://dx.doi.org/10.1016/j.enconman.2024.118068.

[62] Fan R, Xi H. Energy, exergy, economic (3E) analysis, optimization and comparison of different carnot battery systems for energy storage. Energy Convers Manage 2022;252:115037. http://dx.doi.org/10.1016/j.enconman.2021.115037.

[63] Tassenoy R, Couvreur K, Beyne W, Paepe MD, Lecompte S. Techno-economic assessment of carnot batteries for load-shifting of solar PV production of an office building. Renew Energy 2022;199:1133–44. http://dx.doi.org/10.1016/j.renene.2022.09.039.

[64] McTigue JD, Farres-Antunez P, J KS, Markides CN, White AJ. Techno-economic analysis of recuperated Joule-Brayton pumped thermal energy storage. Energy Convers Manage 2022;252:115016. http://dx.doi.org/10.1016/j.enconman.2021.115016.